The assessment of the mechanical and physical properties of in situ timber

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Abstract

The estimation of the properties of in situ timber elements is an essential part of the structural appraisal of many existing buildings and structures around the world. Current methods of doing this are (i) inappropriate, as they utilise visual grading codes of practice intended for use on large batches of new timber and not for use on individual pieces of timber, (ii) inaccurate, as the visual grading parameters used are only weakly correlated with timber's mechanical and physical properties, and finally, (iii) imprecise, as they utilise strength classification, which groups all timber into a small number of classes with associated characteristic properties. Additionally, no current methods of NDT nor SDT adequately account for the immense variability of in situ timber in the UK to estimate properties in accordance with the Eurocodes. Therefore, better methods are needed.

This study (i) researches the contexts and background of in situ structural timber in the UK and (ii) takes a practical structural engineering approach to develop models that combine visual observations, NDT and SDT to estimate characteristic values of MoE, MoR and density, in a manner consistent with the Eurocodes and in a way that accounts for the variability of in situ timber. This exploratory study also demonstrates the ineffectiveness of the practice of treating knots as voids, as the resulting strength reduction factors are shown to be only very weakly correlated with MoR (regardless of whether the factors are derived from first principles or calculated using the US code ASTM D245).

Statistical techniques such as quantile regression (and bootstrapping to find the confidence intervals around quantiles) are applied to timber data in a novel way to develop new predictive models. New knot measures and ratios are developed with predictive powers superior to current measures and ratios. Significant factors such as selection bias and potential prior grading and the deterioration of wood during its life in service are considered and accounted for in novel ways in relation to the models. The study is based on a sample of new UK grown structural sized timber joists of four lesser used species (n=527) and so, further work is required to improve the models. The most useful outcomes of the study are (i) a methodology for the appraisal of the properties of in situ timber in accordance with the Eurocodes and (ii) an outline of what is required in the future to improve them.

Acknowledgements

This study makes use of data from two other studies. The first is based on four minor species grown in the UK and is described in the thesis of David Gil-Moreno (2018). Gil-Moreno's research was financially supported by Forestry Commission Scotland, Cyfoeth Naturiol Cymru (Natural Resources Wales) and Scottish Forestry Trust. All laboratory testing was done in the original work. The job of measuring knots was a joint task carried out as part of the four minor species study and this one. Visual grading was carried out as part of this study.

The second data set comprises Sitka spruce and the results of testing carried out by Edinburgh Napier University (Lyons *et al.*, 2007). All laboratory testing, photographing of knots and transforming images to tables of measurements was done in the original work. The digitised information was interpreted and visual grading carried out as part of this study.

I am grateful for the thoughtful and expert help provided by my supervisor, Dan Ridley-Ellis (Edinburgh Napier University).

Author's declaration

I, the author, declare that this thesis is my own, except where assistance has been acknowledged or stated otherwise. This work has not been submitted for any other degree or qualification.

[redacted]

Mike Bather, March 2022

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Terms, abbreviations and acronyms

A short list is provided here. Other abbreviations and definitions are described as they appear in the text.

Knot clusters comprise all knots within a specified length along the span of a joist accounting for overlapping of knots

Knot groups comprise all knots within a specified length along the span of a joist ignoring overlapping of knots

b is the horizontal width of a joist in vertical edgewise bending

h is the vertical height of a joist in vertical edgewise bending

LCL is the lower two sided 50% confidence limit

MoE is the modulus of elasticity or bending stiffness

MoE_{dyn} is the dynamic modulus of elasticity

MoE_{LCL} is the 50% two sided lower confidence limit of the mean of MoE

MoR is the modulus of rupture or bending strength

MoR_{LCL} is the 50% two sided lower confidence limit of the 0.05 quantile of MoR

n is the number in a sample

OLS is ordinary least squares

r is the correlation coefficient (based on OLS regression)

r^2 is the coefficient of determination

RoG is the rate of growth

ρ is density

ρ_{LCL} is the 50% two sided lower confidence limit of the 0.05 quantile of density

SoG is the slope of grain

Chapter 1 Introduction

1.1 Introduction

1.1.1 Introduction to the thesis

The estimation of the properties of in situ timber elements is an essential part of the structural appraisal of many existing buildings and structures around the world. Current methods of doing this are inappropriate, inaccurate and imprecise. This study researches the contexts and background of in situ timber in the UK and looks at the potential for combining visual observations, NDT and SDT to predict the characteristic values of the key mechanical and physical properties of individual, in situ, structural timber elements.

Due to the vast extent of the population of in situ timber and its variety, this study is an exploratory one, as opposed to a confirmatory one, looking at several possible answers to the key questions of the thesis, suggesting modelling approaches and methods to be tested or developed by later confirmatory studies. Approaches with strong potential for usefulness are presented alongside approaches which show only weak potential.

The unique contributions to knowledge arising from the work are:

(i) The development of new knot measures and ratios with predictive powers superior to current measures and ratios (Chapter 5)
(ii) The consideration and accounting for significant factors such as selection bias and potential prior grading and the deterioration of wood during its life in service in relation to the predictive models (Chapter 7)
(iii) An outline of what is required in the future to improve the outcomes of this study which is based on a limited sample of new UK grown structural sized timber joists (Chapter 7)
(iv) The application of statistical techniques such as quantile regression and bootstrapping (to find the confidence intervals around quantiles) to timber data in novel ways (Chapter 8)

(v) The development of a methodology for the creation of new predictive models for the appraisal of the properties of in situ timber in accordance with the Eurocodes (Chapter 8)

1.1.2 Introduction to the chapter

This chapter begins with a discussion of the shortcomings of existing practice in the appraisal of in situ timber and its economic and environmental background. Next, the aims and objectives of the study are presented and its approaches are justified. Finally, an outline of each chapter in this thesis is presented.

1.2 Background and need for research

1.2.1 Reusing existing structures and sustainability

The need for structural appraisal of existing buildings goes hand in hand with renovation, repair and maintenance. One key industry publication estimates that renovation, repair and maintenance account for 40% of the output of the UK's construction industry (CIRIA, 1994) and comments that a significant proportion of this relates to structural work.

Vast sums of money are spent on repair (RICS, 2021), maintenance and refurbishment of existing structures each year, and many of these buildings and structures contain structural timber. Residential and non-residential low-rise buildings and structures in the UK commonly make use of structural timber, and this form of construction makes up the main part of the total asset value of the built environment (Green, 2014).

It has been shown that the refurbishment of existing buildings is a more sustainable option than demolition and reconstruction as it leads to significant reductions in CO_2 emissions (Plimmer *et al.*, 2008). Additionally, the benefits of refurbishment (in comparison to new construction) extend beyond CO_2 emissions and reduced energy expenditure (BRE, 2016): (i) less raw materials, (ii) less waste, (iii) heritage conservation and community retention and finally, (iv) well restored buildings have a high economic value.

Sustainability is a key driver in the built environment, increasing the extent of reusing existing structures, reducing the carbon footprint of the construction industry and extending the life of building materials (which also addresses material shortages). These issues are worldwide and it is hoped that the conclusions of this study, focussed on appraising in situ structural softwood for reuse in the UK, will be applicable to other countries too.

In summary, the UK contains a wealth of existing buildings and structures, both residential and non-residential, of varying sizes and of varying constructions, with many including structural timber. Their repair and maintenance already form a significant part of our economy and for various strong reasons, more refurbishment of these buildings and structures will be taking place in the future.

1.2.2 Need to determine mechanical and physical properties

The many reasons for a structural appraisal of a building or structure are given by the Institution of Structural Engineers (IStructE, 2010) and are listed below:

- *purchase, insurance, or legal purposes*
- *change of use or loading regime*
- *defects in design and construction*
- *deterioration with time or from being in service*
- *accidental, fire or other damage*
- *assuring safety and/or serviceability for future use*
- *structural alterations*
- *change of environmental conditions*

As noted in the previous sub-section, many existing buildings contain structural timber. Therefore, for structural engineers to carry out their structural appraisals safely, efficiently and sustainably, there is a need for the mechanical and physical properties of individual in situ timber elements to be estimated.

A large proportion of the building stock in the UK was constructed during the 18^{th}, 19^{th} and 20^{th} centuries, while the country prospered from the industrial revolution and cities expanded (Morgan, 1984). None of these structures were designed using modern codes of practice and timber elements were typically sized by carpenters, based on their experience and judgement. Relatively few records remain of this period.

Over the centuries, the construction industry has operated, as it does now, to make a profit and to avoid the unnecessary expense involved in the over-sizing of structural elements such as floor joists (although this may be less applicable for prestigious buildings where expense was relatively less important). Thus, carpenters would typically size timber elements to be adequate and no more. Inevitably this will have led to some elements being under-sized and many being borderline adequate for their anticipated loading. Additionally, bearing in mind the many reasons for structural appraisal listed above, the timber elements in question may be subject to additional future loading or may have been subject to deterioration, decay or damage since they were first fixed in place, thus reducing their original level of structural adequacy.

The cost of installing, for instance, a timber floor in a new build property is significantly lower than the cost of replacing an in situ timber floor in a similar existing property. Refurbishment costs build up due to: (i) removal and reinstatement of ceiling and floor coverings (and possibly services too), (ii) possible temporary propping while an entire floor is removed, (iii) problems of manoeuvring large construction elements within an existing structure (often by hand), (iv) removing defective materials and waste disposal, etc. The monetary costs are compounded by time costs too. In short, replacing structural elements is expensive.

Thus, it is often the case that in situ structural timber elements under consideration may well be borderline structurally adequate/inadequate and there are strong economic and other reasons for a structural appraisal to prove the adequacy of these elements and retain them in position. So, it is important for the structural engineer to obtain reliable and precise estimates of the mechanical and physical properties of the in situ structural timber elements, their spans, and their loads. Broad brush lower bound estimates of strength or stiffness will likely lead to unnecessary and costly replacement of these elements (Williams, 2015), which will also adversely impact on their carbon footprint.

As is always the case for the design of structures, structural engineers work within a regulatory framework that requires them to demonstrate the structural adequacy of their designs and this is typically done by showing compliance with current national and international design codes. The British Standards Institution have now superseded and withdrawn all previous British codes of practice for the design of timber, which were based on permissible stress design, whereby a single hidden factor of safety is applied to derive permissible stresses which are then compared to the working stresses due to estimated actual loads.

Now, the suite of Eurocodes codes is published and maintained, and the structural design of timber is based on limit state design methods. In limit state design, two separate factors of safety are firstly used to derive applied design loads and secondly used to reduce the characteristic strength of a structural element. As the partial factors are clearly presented and, as this is the method used by practising structural engineers in the UK, it is most useful if the mechanical and physical properties of in situ structural timber elements can be obtained in a form that complies with the Eurocodes.

Currently, the methods used in the Eurocodes for timber design (CEN, 2006) are reliant on several separate documents that detail the manner in which mechanical and physical properties are described, measured, statistically adjusted and used in designs (CEN, 1995, 2003a, 2003b, 2010, 2012b, 2013a, 2016b, 2016a, 2019a). Any method for the prediction of the mechanical and physical properties of in situ timber should, as far as is possible, function in accordance with the relevant Eurocodes and, where this is not possible, should be complementary and non-contradictory.

Additionally, the current system of strength classification used in the Eurocodes (CEN, 2016b) groups together grades, species and sources with similar strength properties. The characteristic values of bending strength, modulus of elasticity and density are used to classify timber into 12 strength classes. To achieve a strength class, each characteristic value must be equal to or exceed the minimum values specified for that strength class. Therefore, a timber joist with low characteristic density could be classed as say C14 (a low strength class), even though both its characteristic strength and stiffness could be adequate for say C24 (a higher strength class). Using the current strength classification system requires a designer to use the lower values of strength and stiffness associated with C14.

For new build construction, this is a minor problem that is offset by the advantages that the simple strength classification system brings. For renovation or repair construction, particularly where the structural adequacy of in situ timber elements is borderline, this could lead to adequate timber members being classified as inadequate and requiring replacement. So, using a strength classification system to assess in situ timber is bad for both economic and sustainability reasons. It would therefore be useful if any new system for assessing the mechanical and physical properties of in situ timber elements could operate without placing individual timber elements into classes or groups but instead simply presented the separate characteristic values of bending strength, modulus of elasticity and density.

1.2.3 Current practice is inappropriate, inaccurate, and imprecise

In the UK, there is a widespread agreement among structural engineers on the method of assessment of in situ timber, which is a combination of using a visual grading code of practice with the exercise of engineering judgement (see sub-section 2.7.1). Of the two UK visual grading codes for softwood, the older, withdrawn and superseded British Standard Code of Practice CP112:Part 2:1971 (BSI, 1971) is generally preferred over the newer BS4978 (BSI, 2017) as its grading rules can be more readily applied to in situ timber. Comments on CP112 below are generally applicable to BS4978 or any other visual grading code of practice.

The visual grading code CP112 is inappropriate for the appraisal of in situ structural timber elements for a number of reasons: (i) it was created to visually grade consignments of new timber for construction and not to estimate the properties of an individual element of in situ timber (these two tasks may superficially appear similar but are quite different from a statistical perspective), (ii) the limited samples on which the code is based are not representative of the population of structural timber in the UK which comprises around three centuries of timber imported from around the world, (iii) the statistics in the code assume a normal distribution of strength and stiffness values, make use of z values as opposed to t values and are moderated with obscure factors of safety to create design values for stress and stiffness that do not directly relate to the Eurocodes.[1]

The method is inaccurate primarily because the visual grading code is based heavily on the visible characteristics of the timber in question (e.g. knots, slope of grain and rate of growth) and these visual characteristics have low predictive power. The method is also imprecise because the visual grading code allots all timbers into just four different grades plus a reject category. CP112 was superseded by BS4978 which has only two different grades plus a reject category. This broad brush approach is appropriate for new timber (as it provides an inexpensive, albeit conservative, method of classifying structural timber, which is readily understood and used in the construction industry) but the approach is overly imprecise for assessing in situ timber elements.

The approach adopted by structural engineers in the UK is similar to researchers from the rest of the world and many research papers make use of visual strength grading to assess in situ timber properties. In Europe, there is even a code of practice which promotes this approach; EN17121 describes how the strength reducing characteristics (knots, slope of grain and fissures) used in the strength grading of new timber should be applied to existing timber elements, with new nationally created codes of practice (Macchioni *et al.*, 2019).

Currently, there is no codified guidance in the UK on this topic, although, some countries such as Italy (UNI, 2004) and America (Anthony, Dugan and Anthony, 2009) have limited guidance (albeit based around the concept of applying visual grading to existing timber elements).

1.2.4 Need for new methods of appraisal of in situ timber elements

This lack of guidance is compounded by the difficulties of working with timber whose strength is not possible to measure without destroying the timber itself (although an

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[1] z and t values give an indication of how far from the mean a data point is, based on the standard deviation of a distribution. The t values relate to the sample standard deviation whereas the z values relate to the population standard deviation which is unknown for samples of timber.

estimate can be made based on a predictive model or proof load testing) and whose properties are difficult to predict with accuracy, partly due its variability, and its highly anisotropic and heterogeneous nature (Glos, 1995b). It is further compounded by the need to consider in situ timber from different centuries in a wide variety of differing structures, from hardwood framing in prestigious historical properties to softwood roof members in Victorian terraced housing.

Ideally, any new method of appraisal of the mechanical and physical properties of in situ timber elements must tackle the issues raised in the earlier sub-sections in this section. They must:

(i) be appropriate for individual timber elements (or small groups of them)
(ii) provide an accurate and precise estimate of values of mechanical and physical properties
(iii) provide separate values of strength, stiffness and density (not grouped into classes)
(iv) link directly with the suite of Eurocodes that are commonly used in the UK

1.3 Aim and objectives

The aim and objectives of this research are directed towards a practical application at a future date by a structural engineer tasked with appraising the mechanical and physical properties of timber elements built into an existing structure. Thus, this study attempts to link measurements which can reasonably be obtained on site with the codes of practice that practising structural engineers make use of in structural design. It is hoped that this work will help the construction industry to move towards a more accurate and sustainable approach to the treatment of existing timber.

The aim of this exploratory research is to create new preliminary models for the prediction of the mechanical and physical properties of individual timber elements using a combination of visual and non-destructive and semi-destructive techniques.

The objectives of the research are as follows:

Obj.1. Carry out a literature review to understand the contexts and the background of the assessment of the mechanical and physical properties of timber in existing structures.

Obj.2. Obtain measurements from the destructive and non-destructive testing of a large sample of structural sized timber joists to determine their mechanical and physical properties.

Obj.3. Understand the statistical methods, used in the Eurocodes, by which the characteristic values of the mechanical and physical properties of timber are calculated from the results of testing samples of timber.

Obj.4. Review the test data, choose the most appropriate measurements, and then build new statistical models to predict estimates (and their lower bound confidence limits) of the mechanical and physical properties of timber elements.

Obj.5. Consider the contexts of the application of the models and derive methods to determine the characteristic values of the properties for direct use in design calculations in accordance with the Eurocodes.

Obj.6. Apply the predictive models to other test data to assess the performance of the predictive models.

1.4 Justification of the approaches taken

As a chartered structural engineer with over two decades of experience in industry, the author approached this work with views formed by the practices of the profession. These practices represent a low level of understanding of wood and its variability. In the author's experience, there is a general assumption that wood's visual features are directly related to its properties and that the effect of knots can be simplified to voids in the cross section of timber elements.

A better understanding of the nature of wood and its variability evolved through the literature review (despite there being many studies using visual grading codes to assess in situ timber elements and authoritative support for the treatment of knots as voids). The key outcome of the literature review was an understanding of the variability of (i) wood, caused by many factors such as species, growth area and forestry practices, and (ii) structural timber, due to national and international trade and politics, appearance grading, construction specifications, region of construction, etc. Unfortunately, the literature review yielded many small scale studies of in situ timber with differing results regarding the efficacy of NDT, SDT and visual features in relation to estimating timber properties. No single best method of measuring knots became apparent, other than knot area ratios, which are impractical for use with in situ timber. Additionally, almost no studies were found that directly related their results to the suite of structural design Eurocodes used by structural engineers.

Several conclusions were drawn from the above regarding the nature of the research work to be carried out.

1. Due to the variability of wood, this study must use a large data set, ideally of several species. A data set (n=527) of four minor species was chosen and used for the research.

2. Due to the multiple factors affecting the properties of in situ timber, it would be impractical to develop a large range of predictive models with each focussing on a particular combination of specific factors, e.g. one species from a single growth area from a specified era of construction. Thus, a single set of predictive models are developed that cover all species, growth areas, etc. together.

3. Without consensus on how knots influence the properties of wood, more investigation was needed to compare theoretical approaches with the results of laboratory testing. Each of the differing knot measures of five national visual grading codes were applied to each test piece in the data set. Additionally, new knot measures, focussing on practical measurement in situ, were developed and checked in a similar way. Finally, the notion that knots behave as voids within cross sections of timber was investigated through calculating the reduced section properties of each test piece of the data set.

4. The impossibility of creating a sample that is representative of in situ structural timber in the UK means that any predictive models for in situ timber must be developed through combined experimental and observational research. Therefore, firstly, without a representative sample, the sample selection bias of the predictive models must be accounted for. Methods to do this are proposed and discussed.

Secondly, sample selection bias can be reduced in the future through combining more studies to extend the basis of the predictive models.

5. For the predictive models to be of use to a practising structural engineer, they must link directly to the suite of the structural design Eurocodes. The statistical processes used to create the predictive models follow as closely as possible the processes used in the Eurocodes to determine the characteristic values of timber. Additionally, where possible for the models, simplicity is preferred to complexity.

6. To a limited degree the predictive models have been successfully verified, using a second data set of a different species (n=60). This is not and even repeating this process multiple times with other fresh data sets, it can never be sufficient to fully demonstrate the effectiveness of the models for all species, all growth areas, all eras of construction, etc. Of more importance is to demonstrate the validity of the methods proposed in the development of the models. The discussions around this comprise an entire chapter of the thesis and cover the contexts within which the predictive models will be applied.

7. Structural appraisal is carried out on a range of sizes of structures with varying levels of accessibility and to varying budgets. So, having a range of predictive models available to practitioners is an advantage. By separating out the measurements of SDT, NDT and visual features, several models are developed using single or combining multiple predictor variables. The power of these models varies and methods are developed to compensate for the weaker models and to differentiate between models, thus giving flexibility to practitioners on site.

1.5 Thesis: outline of chapters

Chapter 1 introduces the thesis and explains the background of the appraisal of the properties of in situ structural timber elements; the need for it and its current shortcomings (Obj.1).

Chapter 2 comprises a literature review (Obj.1) which firstly explains the anatomy of softwood trees, the features and the chemical make-up of their wood. Secondly, the key mechanical and physical properties of softwood timber are described with particular emphasis on their variability and their inter-relationships. Thirdly, a brief overview of the historical sourcing and use of timber in the UK is presented together with a discussion of the ways that this timber varies over time and how the properties of wood change as time passes. Finally, the basis of the appraisal of in situ structural timber is discussed together with the methods currently used in the UK, Europe and the USA.

Chapter 3 defines the materials and the methods used in this study. The first part of the chapter focusses on the collection and preparation and testing of a sample of test pieces of four minor species (n=527) (Obj.2) and the second part focusses on the statistical techniques currently used in grading new batches of timber and other techniques that could potentially be used in assessing the characteristic values of key properties of in situ timber elements (Obj.3).

Chapter 4 covers the use of visual grading codes. Firstly, key European ones are introduced and reviewed (Obj.1) and secondly, these codes are applied to the minor species data set and their performance is discussed in relation to this thesis.

Chapter 5 reviews currently used visual grading parameters and, finding little consensus, new methods of measuring knots are developed (Obj.4). Additionally, the relationships between the old and new visual grading parameters and the mechanical and physical properties of timber are explored. Finally, the current practice of treating knots as voids (as used in the USA) is assessed using the minor species data set.

Chapter 6 comprises a focussed literature review of NDT and SDT parameters in relation to the prediction of the mechanical and physical properties of in situ timber (Obj.1).

Chapter 7 presents a discussion on the contexts, assumptions and approaches of the predictive models under development in this study, such as, the differences between distribution and regression models, selection bias, prior grading and an assessment of the quality of desk study and SDT, NDT and visual inspection information (Obj.5).

Chapter 8 describes the building of new predictive models for the estimation of the 50% two sided lower confidence limits of the mean of MoE and the 0.05 quantiles of density and MoR for individual timber elements (Obj.4). Also, for MoE and MoR, the models are trialled on a different data set comprising Sitka spruce (n=60) (Obj.6).

Chapter 9 concludes the thesis, discussing its application and its implications and associated further work.

Chapter 2 Literature review

2.1 Introduction to the chapter

This literature review presents an introduction to the way that a tree grows and how this affects the chemical composition of its wood and the wood's characteristic features. Next, the mechanical and physical properties of timber are considered, their variation and the way that they relate to one another. A brief overview of the way that timber has been sourced in the UK over the last three hundred years lays the foundations for understanding the immense variety in the population of timber elements in existing structures in the UK (including a wide range of species and growth areas). A summary of research into the possible deterioration of timber due to ageing, load duration effects and biological damage is presented and then finally, the appraisal of in situ timber is considered from practical and systematic viewpoints. This literature review is extended in later chapters with smaller, more focussed literature reviews, in particular in Chapter 4 and Chapter 6.

The topics of this review are chosen and described in a way to illustrate the immense variability of the composition of wood and the structural performance of timber. Visual grading codes are introduced at this stage as they form the basis of current methods of assessment of in situ timber elements. The relationships between those parameters of timber that can be measured and the mechanical and physical properties are presented and discussed further in Chapter 4 and Chapter 5.

2.2 Introduction to trees and wood

2.2.1 Variation in tracheids in a softwood tree

Many standard textbooks present detailed explanations of the anatomy of a softwood tree, for instance Dinwoodie (2000). This sub-section focusses on just some of the variations seen within the stem of a softwood tree, considering tracheid cells to illustrate variability in structural timber.

The tracheid cells in the stem are long and thin, being between 100 and 200 times longer than they are wide, and are responsible for the main part of the tree's density and strength and stiffness in bending (Panshin and de Zeeuw, 1980). The tracheid cells that grow during the earlier and wetter period of annual growth have thin cell walls and wide lumina, suited to the transmission of sap (earlywood). The cells that grow later in the growing season have thicker and stronger cell walls with corresponding narrow lumina (latewood). Latewood cells can be around twice as dense as earlywood ones.

Groups of tracheid cells can also be differentiated into juvenile wood and mature wood. Juvenile wood extends the full length of a tree trunk, being the first several growth rings around the pith at any point. Its fibres are generally shorter than those of mature wood, found elsewhere in the stem of the tree and is characterised by shorter tracheid length, more earlywood in growth rings, more compression wood, less cellulose and more lignin in the cell walls of the tracheids. Thus, juvenile wood may be both denser and weaker than mature wood.

Juvenile wood can differ significantly from mature wood, more so in pines and less so in spruces, but so much so, that it could be considered to be a different wood entirely. This difference could be between (i) wood close to the pith versus close to the outer bark or (ii) between wood near the base of the tree versus near its top (Zobel and van Buijtenen, 1989).

Additionally, the cellulose microfibril angle (see sub-section 2.2.3) in juvenile wood is generally lower than in the mature wood, varying from around 35 degrees at the pith to around 15 degrees at the 20th growth ring from the pith in UK Sitka spruce (Moore, 2011). Again, considering UK Sitka spruce, as an illustration, the length of tracheids vary from just over 1mm at the pith to just under 3mm at the 20th growth ring from the pith (Moore, 2011).

Thus, it is seen that the nature of wood itself in a single tree, varies from top to bottom and from pith to the outer growth rings. The composition of the various elements within the wood of different trees (for instance young trees and old ones) differs and so do their overall properties. All this is influenced not just by species, but also by forestry practices and growth conditions, which themselves vary from one time period to another and from one region to another.

2.2.2 Other features of softwood

Variation in softwood can also be seen in many of its features, such as:

i. Slope of grain, spiral grain and interlocking grain – how the grain in wood varies from the alignment of the longitudinal axis of a piece sawn from the trunk
ii. Knots - branches growing in the living tree appear as knots in converted timber
iii. Rate of growth - the extent of annual growth which can be measured from the exposed sawn end grain of a converted piece of timber
iv. Juvenile wood - approximately identified using the naked eye as being bounded by the first 20 rings closest to the pith of a log
v. Anisotropy - the overlapping parallel arrangement of the tracheid cells along the length of a log leads to significant differences in strength and stiffness between the longitudinal and transverse directions of timber elements
vi. Compression wood - a type of reaction wood found in softwood trees, which occurs as a result of externally applied forces to the tree, such as wind pressure
vii. Collapse - a drying defect that occurs as free water is removed and creates significant volumetric shrinkage

Several of these visible features are known to correlate weakly with the mechanical and physical properties of timber. With no other easily measurable visible characteristics to use, these features have over time been incorporated in the visual grading of softwood, which may have given the general impression among users of the grading rules that the correlations are stronger than they actually are. The complex interaction of the different features described in this and the following sub-sections mean that no one particular visual feature of wood predicts well its mechanical and physical properties. Additionally, the combining of visual features barely increases predictive power.

2.2.3 Chemical make-up of softwood

The chemical make-up of wood is dealt with well in several textbooks (for instance, Desch and Dinwoodie, 1981) and so is dealt with only briefly here. There is a range of factors in the make-up of softwood apparent at a range of levels (varying from (i) the molecular, through (ii) that visible using a microscopic, to (iii) that visible to the naked eye) that are influenced by the development of each individual tree as it grows. When its cambium reproduces to create new xylem cells, it is not possible to control their molecular make up, or the ratio of their different chemical compounds or the lengths of the cellulose molecules or the angles of the microfibrils in the three layers of the cell walls. As a living organism, each tree creates wood in its own way, influenced by its environment (forestry practices such as planting spacings and thinning, the climate and the soil) and genetic make-up (its species or sub-species).

Some of the ways that sawn timber pieces are different to one another can be seen with the naked eye (e.g. knots, SoG, RoG) but most of the ways are invisible to the naked eye (lengths of tracheid cells, thicknesses of tracheid cells, lengths of cellulose molecules, the orientation of microfibrils in the three cell walls of the tracheid cells and the relative quantities of lignin, hemicellulose and cellulose).

Not only are many of the differentiating factors unknowable to wood scientists, but they are also all (apart from the visible ones), for reasons of time and cost, unknowable to a structural engineer surveying a timber building. Visual grading is based on the premise that those features that are visible correlate with the many invisible factors in the complex chemical and physical nature of wood because both are influenced by the growth conditions of the tree.

Figure 2.1 is a slide from a presentation delivered at the Shatis'19 conference (Bather and Ridley-Ellis, 2019). This gives a visual summary of the above. The weakness of the correlations between the visual features and the unknowable factors affecting the mechanical and physical properties is considered in Chapter 5 and here, it is worth noting that the causes and the extent of variability in the population of in situ timber is such that the assessment of individual in situ elements cannot be carried out in the same manner as the assessment of batches of new timber of defined species from defined growth areas.

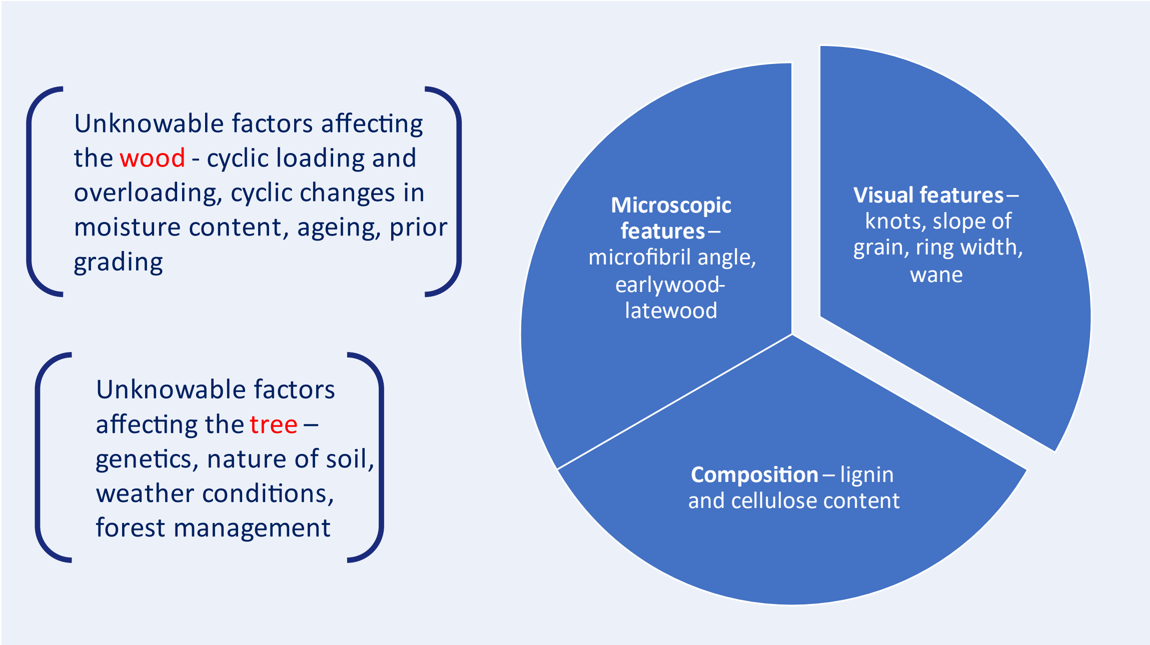

Figure 2.1. Simplified visual summary of the sources of the variability of in situ timber's mechanical and physical properties

Finally, in this sub-section, the presence of water in wood, i.e. moisture content, is considered. This varies according to temperature and humidity of the air. Additionally, as wood is hygroscopic, it tends to absorb moisture when in contact with water or damp materials (particularly when end grain is exposed). The lumen of each cell is linked to others with pits that allow the passage of water from one cell to another. Kiln dried softwood may have a moisture content of 18 – 20% on delivery to a construction site and then, in a heated internal environment, may dry to 10 – 15% moisture content (TRADA, 2007). The moisture content of an in situ timber element will vary according to the weathertightness of its structure, the season and recent weather, the use of the structure and the location of the timber within the structure.

The long chain cellulose and hemicellulose molecules in the cell walls of wood are hygroscopic, being able to adsorb water. The adsorbed water fits between the polymer chains and increases the distance between the chains, thus swelling the width of the cell wall. The degree of the adsorption of water in the cell walls of wood significantly affects its density, bending strength and stiffness and as such must always be accounted for.

2.3 Introduction to the mechanical and physical properties of wood

2.3.1 Key mechanical and physical properties of structural timber

In order to design new timber structures (CEN, 2006; Building Regulations, 2010) and to assess existing ones, in accordance with the current design codes of practice, a structural engineer in the UK needs to know a small number of basic mechanical and physical properties of the timber in question. These are presented in Table 2.1, along with the manner of their determination.

Clearly, the properties of bending strength and stiffness are required for the structural assessment of timber elements in bending. It is seen in Table 2.1 that the density of timber is only of direct use in design for fire performance and for the design of connections: (i) metal type dowel connections including nails, screws, bolts, and dowels, and (ii) simple bearing connections. So, as this encompasses all typical timber connections, it is seen that density is a property that is also routinely required for design checking.

In considering the end uses of timber, and for many years, density is and has been a key indicator for pulp yield and pulp quality for paper, energy yield from biomass and structural strength and stiffness (Zobel and van Buijtenen, 1989). Its ubiquity in research papers is due to its ease of measurement and its general usefulness, despite it typically being only moderately effective (at best) as a predictor of bending strength and stiffness.

The mechanical and physical properties of softwood are considered to be adequately strongly related to one another (Glos, 1995a) such that several properties presented in Table 2.1 need not be measured directly but can be calculated from other known properties. The advantage of this is the avoidance of expensive and time consuming testing but the disadvantage is that the relationships are necessarily conservative. Additionally, from the perspective of this study, it is not known if these relationships remain valid for old, in situ timber. In the case of the Eurocodes, several characteristic values can be calculated from other characteristic values (CEN, 2010). The green shaded rows of Table 2.1 table must be determined directly as part of the establishment of the grading process and the remaining properties can be calculated from these grade determining properties.

Table 2.1. Mechanical and physical properties of timber: their notations, derivations and uses (Porteous and Kermani, 2007; Draycott and Bullman, 2009; CEN, 2016b). Notation suffixes are as EN338.

Strength properties in N/mm^2		Derivation	Notes
Bending	$f_{m,k}$	Determined from tests	Beam bending capacity (strength class determining parameter)
Tension parallel	$f_{t,0,k}$	Calculated using $f_{m,k}$	Tie tension capacity
Tension perpendicular	$f_{t,90,k}$	Constant value of 0.4 adopted	
Compression parallel	$f_{c,0,k}$	Calculated using $f_{m,k}$	Strut compression capacity
Compression perpendicular	$f_{c,90,k}$	Calculated using ρ_k	Bearing capacity
Shear	$f_{v,k}$	Calculated using $f_{m,k}$ or constant of 4.0 adopted	Shear capacity
Stiffness properties in kN/mm^2			
Mean modulus of elasticity parallel bending	$E_{m,0,mean}$	Determined from tests	Bending deflection and floor vibration (strength class determining parameter)
5 percentile modulus of elasticity parallel bending	$E_{m,0,k}$	Calculated using $E_{m,0,mean}$	Strut compression capacity
Mean modulus of elasticity perpendicular	$E_{m,90,mean}$	Calculated using $E_{m,0,mean}$	
Mean shear modulus	G_{mean}	Calculated using $E_{m,0,mean}$	Bending deflection
Density in kg/m^3			
5 percentile density	ρ_k	Determined from tests	Connection capacity and fire performance (strength class determining parameter)
Mean density	ρ_{mean}	Calculated using ρ_k	

It should be noted that the conversion equations referenced in Table 2.1 are intended for use in relation to EN338, i.e. strength classes for softwood in bending which makes use of broad brush classes. They are not presented in the Eurocodes as being for use on individual timber elements with varying key characteristic properties. It is assumed that their use can be extended to this additional purpose (albeit giving conservative results), but this is an assumption that needs to be confirmed.

This research focusses on the three properties that must be determined from tests. As these three properties can be used to calculate the remaining timber properties, this could be considered sufficient for a structural appraisal of a timber structure. However, it may prove worthwhile for a structural engineer to measure directly one or more of the remaining timber properties, especially if the structural adequacy of the timber elements in question are borderline (since the relationships are so conservative).

One additional key property of timber (not included in the above table) is its moisture content, due to its effects on wood’s mechanical and physical properties and durability. A higher moisture content leads to reduced strength and stiffness and increases the amount of deformation due to creep. A higher moisture content leads to increased risk of fungal and insect attack, particularly when certain threshold values are crossed (around 20% moisture content).

2.3.2 Variation of mechanical and physical properties

The production of different types of cells within wood is controlled by auxins during cambial development. Auxins in turn are controlled by the interaction of environmental and genetic factors, compounded by factors within a tree such as distance from the crown, cambial age, the location of a cell within an annual growth ring and the maturity of the tree (Zobel and van Buijtenen, 1989); hence the variation within and between trees.

Based on a review of several research papers, the correlation of the anatomical features and properties of wood has been found to be variable and often weak (Zobel and van Buijtenen, 1989). For instance, density and tracheid length vary independently between trees and have a very weak relationship; density is similarly unrelated to fibril angle; tracheid length and width are strongly related in some trees and very weakly related in others of the same species. Finally, density and tracheid width are known to have a moderate relationship and tracheid length and microfibril angle have a negative moderate relationship.

The distribution types and coefficients of variation (CoV) for the mechanical and physical properties of European softwood are given in Table 2.2, extracted from the

JCSS[2] Probabilistic Model Code. The greater the CoV, the greater the variation and so it is seen that the variation in MoR is greatest (almost double that of MoE and density).

Table 2.2. Distribution types and coefficients of variation for European softwood (JCSS, 2006)

	Distribution	CoV
Bending strength (MoR)	Lognormal	0.25
Bending stiffness (MoE)	Lognormal	0.13
Density	Normal	0.1

The CoV values in the table relate to ungraded timber. As timber bending strength increases, the degree of variation reduces, with the higher strengths reducing the most, as is shown in Figure 2.2, extracted from a report by Ranta-Maunus on Finnish timber (2007) and showing characteristic bending strengths for both spruce (*Picea abies*) and pine (*Pinus sylvestris*).

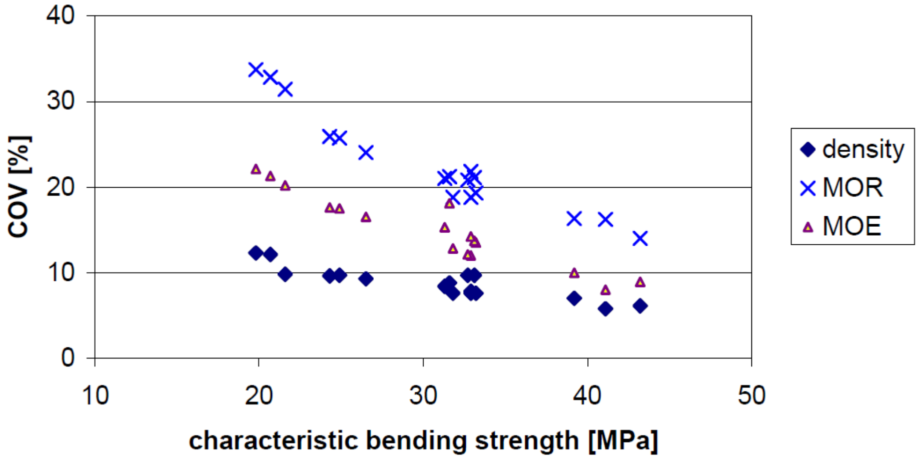

Figure 2.2. CoVs in relation to characteristic bending strengths (Ranta-Maunus, 2007, p. 20)

In the Eurocodes, strength parameters are *"…assumed as logarithmically normally distributed unless analysis of the data shows that a normal distribution is more appropriate."* (CEN, 2016a), density is assumed as being normally distributed, again in accordance with Table 2.2, and MoE is assumed to be normally distributed. These

[2] JCSS is the Joint Committee on Structural Safety in the field of structural related risk and reliability, acting on behalf of six international professional associations (such as IABSE, CIB and RILEM). Thus, the global estimates of CoV in Table 2.2 would be expected to be upper bound estimates.

assumptions, are not always clear cut, for instance, the Gradewood project found the bending strength model for spruce to lie in the middle of the linear and logarithmic models (Ranta-Maunus, 2012). These assumptions are important for the parametric[3] distribution statistics used in the visual grading codes and are still important for the boot strapping non-parametric regression models proposed in this study, but less so.

The degree of variation of new timber elements, which are tested in discrete batches is expected to be significantly less than the variation of in situ timber. Firstly, the population of in situ timber has been formed over several centuries and so represents different climatic periods, different phases of forest development, different methods of forestry and cutting and processing timber. These timber elements have been subject to differing service lives over differing lengths of time. Secondly, old timber elements which would need to be tested and reported upon comprise a mix of timber elements in differing states of fungal and insect attack, of varying cross sections which are difficult to model and create further difficulties in testing due to possible twisting and uneven seating at bearings. These factors create further variation in the results of testing when compared with the relatively uniformly produced new timber elements.

2.3.2.1 Density

Density varies the least in Table 2.2, as all softwood trees have the same basic anatomy and constituents of their wood. Even so, as with all mechanical and physical properties, density is still affected by a multitude of factors (such as growth area, latitude, elevation, exposure, fertilisation, stand density, growth rate, species and age). Density is a coarse measure which can be found, giving an average of several factors, such as: the thickness of cell walls, the ratio of earlywood and latewood, the presence of chemical deposits in and around cells (e.g. resins in softwoods), the presence of knots and fissures (Zobel and van Buijtenen, 1989). The cambial age of wood affects the ratio of earlywood and latewood, particularly close to the pith. Thus, the density of

[3] Parametric statistical techniques rely on assumptions about the parameters and distribution of the population; thus, some conditions must be met for parametric tests to be reliable. Non-parametric techniques do not rely on these assumptions.

wood is seen to vary across its cross section, for most commercial softwoods, typically increasing at distances further from a region close to the pith (Moore, 2011). It is worth noting that there is a commonly held view amongst engineering practitioners that density is a useful indicator of MoR and MoE, however, as is shown later in this section, it typically has poor correlations with MoR and MoE.

The Eurocodes settle on a standard measure of density based on a small block of clear wood (free from knots and resin pockets) cut from a larger timber element and dried and measured (CEN, 2012b). Bearing in mind the variation of cell types and thicknesses, varying ratio of earlywood and latewood, knots and fissures within a single structural sized timber element, this standard measure of density will almost never be the same as the overall density of the element as a whole. Nor will it necessarily match the density of another small block of clear wood cut from another part of the element. It is even less likely to match a small block of wood containing knots or fissures.

This inherent variation must be borne in mind when comparing methods of measurement of density. The small block method has the advantage of providing an average density across the full width of a cross section of an element and allowing for variation due to knots and fissures (and visible chemical deposits) to be removed from its measurement and it should provide the lowest of all possible values of density. It is however a measure of only one small part of the element. Measurement based on the whole element includes variation due to knots, fissures, chemical deposits, changes in cell structures, and latewood and earlywood ratios but is more representative of the wood as a whole.

NDT measurement (to estimate density) based on surface indentation or withdrawal loads of inserted screws (see Sub-section 6.2) suffers from the severely limited extent of its measurement (just the surface at one or a few positions). SDT measurements based on drill resistance or core drilling samples similarly suffer from the limited extent of their measurements.

2.3.2.2 Bending strength

The variation of bending strength is affected by not just the overall chemical composition of the wood but also by the arrangement of its molecules (for instance the angle of microfibrils). Similarly, variation in other features such as tracheid length or grain angle significantly affect the variation of bending strength.

The variation in bending strength has been extensively investigated, and recently by the Gradewood Project (a European wide research project spanning several countries and focussing on Norway spruce and Scots pine). The project extended an extensive collection of past studies (around 26 000 results) with a further 2703 destructive bending tests to better understand variation and to improve grading (Ranta-Maunus, 2009; Ranta-Maunus, Denzler and Stapel, 2011). For Norway spruce and Scots pine, mean values and CoVs vary from country to country for MoR, MoE and density as is shown in Table 2.3 which summarises this data from the Gradewood project.

Table 2.3. Maximum and minimum values of means and CoVs from the Gradewood project (Ranta-Maunus, Denzler and Stapel, 2011)

		MoR		MoE		Density	
		Mean	CoV	Mean	CoV	Mean	CoV
		N/mm^2		N/mm^2		kg/m^3	
Norway spruce	Min	34.8	0.26	9600	0.17	387	0.10
Norway spruce	Max	43.7	0.35	12000	0.22	445	0.12
Scots pine	Min	25.6	0.38	10000	0.20	390	0.08
Scots pine	Max	34.0	0.44	12300	0.24	452	0.12

The Gradewood Project demonstrates that variability is such that strength differences between samples cannot be ascribed with certainty to different populations, as opposed to simply arising from statistical error. This raises questions about currently used grading requirements and in particular confidence level requirements.

The Gradewood Project demonstrates that variability of characteristic values within a country is approximately the same as variability between countries, and so equally important, which is contrary to one of the assumptions of the Eurocodes' grading procedures. With regard to grading and characteristic values, the variance of the residuals was shown to be more important than mean values of properties.

An interesting finding was that the variation of characteristic bending strengths of spruce from different growth areas remained within the confidence interval, whereas that of pine was found to exceed this and so its bending strength was shown to significantly vary between growth areas. Figure 2.3 is an illustration from the report of the Gradewood Project which shows the variation of means and ranges of bending strengths for spruce from 14 different European countries.

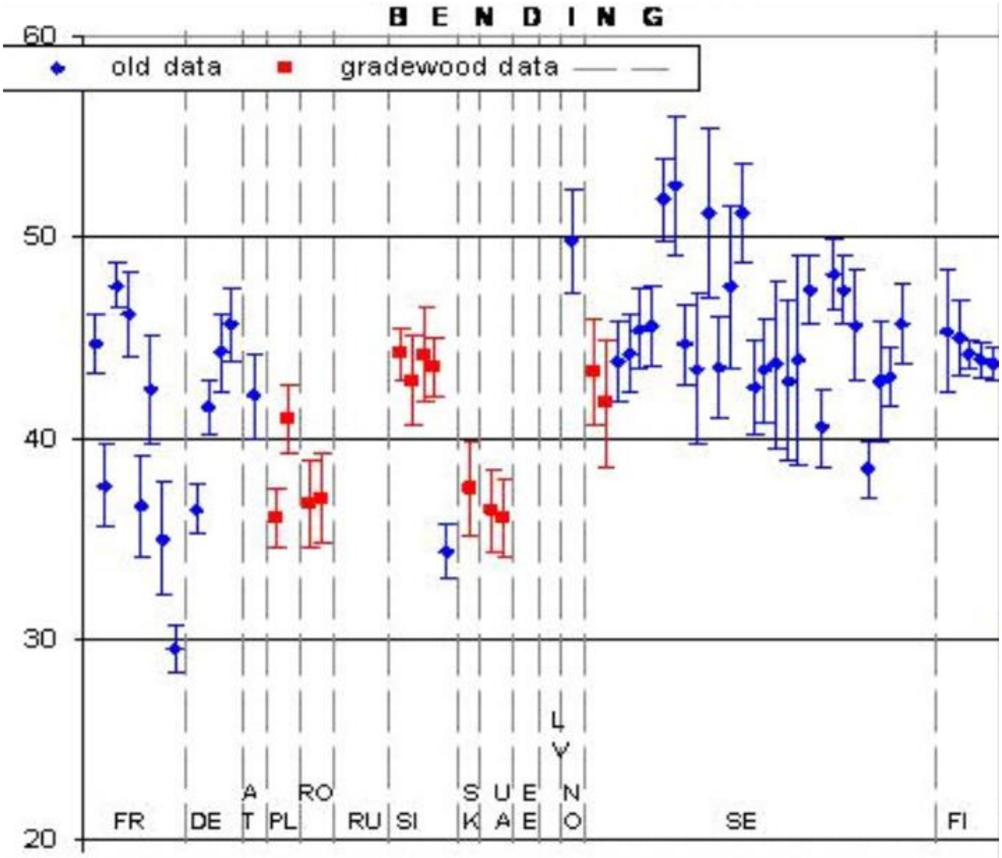

Figure 2.3. Variability of bending strength of spruce samples from the Gradewood Project (Figure 3 of the Final Report [*Grading of timber for engineered wood products (Gradewood)*] (Toratti, 2011). 95% confidence limits are shown by the bars with mean values of samples at their mid-heights. [Bending strength (N/mm^2) along the y axis and countries along the x axis (e.g. FR = France)]

Other studies have shown variation of bending strength between countries can be found to be smaller than within countries and on occasion, smaller than within a single saw mill (Ranta-Maunus and Denzler, 2009). Variation of characteristic bending strength is even greater than for mean bending strength due to the increased CoV of this statistic. Thus, any attempt to quantify variation based on country sized growth areas will overlook the significant variation within countries.

2.3.2.3 Bending stiffness

Although not investigated as intensively as MoR, MoE has been shown in several studies to vary in similar ways. Hoibo *et al.* (2014) found that large parts of this variation (for Norway spruce) are explained by growth site, relative tree size and longitudinal position in stem; although, the inclusion of origin with models for MoE was less important than density (whereas for MoR, origin was the most important). As MoR and MoE correlate with relative tree size within a stand of Norway spruce, but only MoE also correlates with longitudinal position in stem (Vestøl *et al.*, 2012), this can be problematic when predicting MoR from MoE and illustrates how different properties vary in relation to specific factors at differing rates.

For Sitka spruce, Moore *et al*. (2013) found that 25% of the total variation in mechanical properties can be attributed to differences between stands and 75% can be attributed to within-stand variation. This confirms that, once again, within-tree variation is significant.

With regard to the four minor species data set used in this study, it has already been shown that most of the variation in mechanical properties is due to differences within trees, especially for MoR. However, for density, the species was of most importance. Overall, for global MoE, 7% of variance was explained by species, 15% and 10% by the site and plot, 12% by the tree and 63% within-tree (Gil-Moreno, 2018).

A key factor of the within-tree variance is the difference between juvenile wood and mature wood, and the demarcation between the two types of wood varies by species, being under genetic control (Dinwoodie, 2000). However, the demarcation varies according to the method by which it is defined (tracheid length, cellulose microfibril angle or wood density are commonly used) and it has been determined variously as being 10, 12, 15 or 20 years just for Sitka spruce (depending on definition) (Ridley-Ellis, Moore and Lyon, 2008, Moore, 2011). The key property of juvenile wood most strongly related to MoE is the microfibril angle, which is not strongly related to say density and so no demarcation will ever be perfect for all properties.

Summing up, for density, MoR and MoE, their properties vary significantly and at different rates due to several reasons, many of which for in situ timber, are unknowable, demonstrating the complexity of wood and the difficulties of defining strong relationships between these properties that hold true in all circumstances. This issue is dealt with further in the next section.

2.3.3 Relationships between mechanical and physical properties

The key mechanical and physical properties of timber are related and approximate typical strengths of these relationships are given in Table 2.4 which relates to European softwood. The intention of the JCSS report is to provide an authoritative set of figures to be used as Bayesian priors in statistical analyses.

Table 2.4. Coefficients of correlation and determination for key mechanical and physical properties of timber (JCSS, 2006)

	Coefficient of correlation r	Coefficient of determination r^2
MoE with MoR	0.8	0.64
MoE with Density	0.6	0.36
MoR with Density	0.6	0.36

Table 2.4 shows that the relationship between MoE and MoR has the potential to usefully contribute to a predictive model. Whereas the other relationships with density appear to be of less direct use.

2.3.3.1 MoE and MoR relationships with density

Values of the coefficients of determination for MoR and MoE with density are given by Hanhijärvi *et al*. (2005) and are shown in Table 2.5. These are higher than the values presented by the JCSS and higher than the values obtained by Thelandersson and Larsen (2003), ranging from 0.4 to 0.6, for MoE with density. This variation of coefficient of determination is partly caused by the variability of each of the mechanical and physical properties in the relationships, varying species, growth areas, forestry practices, varying sizes of samples, etc. So, it is unsurprising that three different studies have obtained different coefficients of determination (especially for different species).

Table 2.5. Coefficients of determination for key mechanical and physical properties of timber adapted from Hanhijarvi *et al*. (2005, p. 49)

	Coefficient of determination, r^2 spruce			Coefficient of determination, r^2 Scots pine		
	MoR	MoE (local)	MoE (global)	MoR	MoE (local)	MoE (global)
MoR	1			1		
MoE (local)	0.65	1		0.68	1	
MoE (global)	0.67	0.92	1	0.69	0.95	1
Density	0.37	0.50	0.58	0.58	0.65	0.72

For further reference on these and other relationships, the most extensive and recent reports have been created as part of the Gradewood project (Ranta-Maunus, 2009; Ranta-Maunus, Denzler and Stapel, 2011). These reports focus on the grading of new timber, its growth areas and correlations between grade determining properties and indicating properties.

2.3.3.2 MoE_{dyn} relationship with static MoE

The relationship between MoE_{dyn} and static MoE has been investigated several times in the past. Ross and Pellerin (1994) reviewed five studies of structural sized timber and found correlation coefficients ranging from 0.95 to 0.99, with an unweighted average of 0.975. This is a very strong relationship. More recently and with much larger data sets, this relationship has been investigated as part of the Gradewood project. For Norway spruce, the coefficient of determination for MoE_{dyn} and MoE_{global} varies from 0.68 to 0.83 (for MoE_{dyn} calculated using the frequency of longitudinal vibration with an assumed density of 450 kg/m^3 or with measured density). For Scots pine, the coefficient varies from 0.60 to 0.85. Thus, MoE_{dyn} is likely to be a good predictor of MoE.

2.3.3.3 MoE relationship with MoR

The relationship between MoE (tested in flatwise or edgewise bending) and MoR (edgewise bending) has been investigated several times in the past. Firstly, the literature review of Ross and Pellerin (1994) included nine studies of structural sized timber from Canada, UK and USA and found correlation coefficients ranging from 0.57 to 0.87, with an unweighted average of 0.78. An adapted summary of results is presented in Table 2.6.

Table 2.6. Coefficients of determination for the relationship between MoE (tested in flatwise or edgewise bending) and MoR (edgewise bending). Adapted from Ross and Pellerin (1994, p. 14)

Species	Location	Coefficient of determination, r^2
Douglas fir	Idaho, Eastern Washington	0.42
Grand fir	Idaho	0.35 – 0.49
Southern Pine	Southern US	0.32
Norway spruce and Scots pine	Great Britain	0.46
Douglas fir	Inland North-western, US	0.41
Douglas fir	Western Oregon, Washington	0.64 – 0.76
Western hemlock	Western Oregon, Washington	0.71
Douglas fir	British Columbia, Canada	0.55
Western hemlock	British Columbia, Canada	0.49 – 0.59
Noble fir	British Columbia, Canada	0.44
Western white spruce	British Columbia, Canada	0.62
Lodgepole pine	British Columbia, Canada	0.64
White spruce	Eastern Canada	0.61 – 0.71
Jack pine	Eastern Canada	0.48 – 0.53
Southern Pine	Southern US	0.45

Table 2.6 includes eleven species of tree from six different growth areas (covering many of the sources of timber historically imported into the UK) and demonstrates a typically strong relationship between MoE and MoR. Thus, if MoE can be measured well, then it is reasonable to predict MoR from this measurement.

Secondly, the literature review of Kasal, Lear and Tannert (2010) included seven studies of the relationship between static MoE (edgewise bending) and MoR (both flatwise and edgewise bending) and found coefficients of determination ranging between 0.32 and 0.76 with an unweighted average coefficient of determination of 0.49 This is significantly less than the figures in the JCSS report and the values found by Ross and Pellerin.

Additionally, once again making use of the extensive Gradewood data, the relationships between MoE and MoR for Norway spruce are plotted for five different countries, with different growing environments and forestry practices. Refer to Figure 2.4, the similarity between the results is apparent and suggests that the relationship between MoE and MoR could be a useful element in a predictive model.

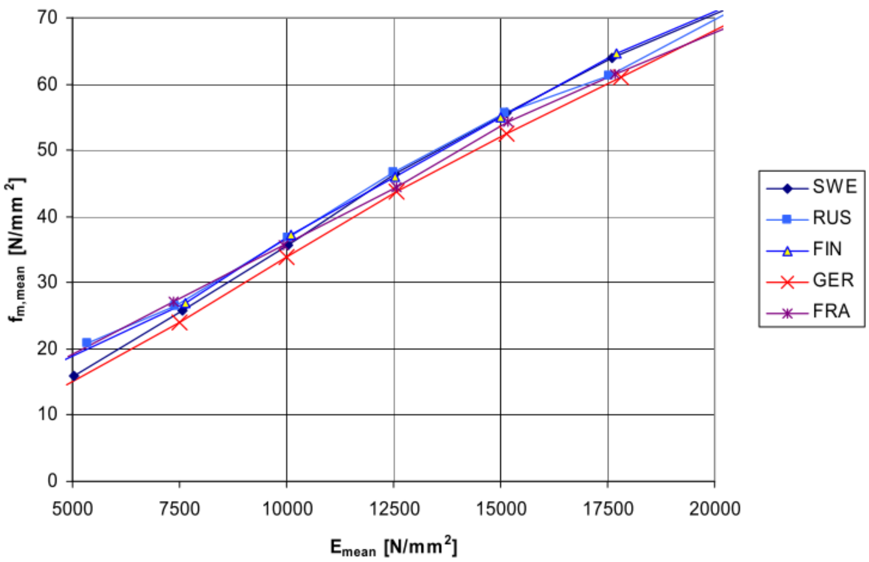

Figure 2.4. Mean bending strength versus mean modulus of elasticity for Norway spruce from different countries (Sweden, Russia, Finland, Germany, France) (n=13548) (Ranta-Maunus and Denzler, 2009, p. 4)

Finally, also from the Gradewood project, a graph is presented in Figure 2.5, showing linear regression lines for MoE_{dyn} (using a standard density of 450 kg/m^3) and MoR. The varying slopes and intercepts of the different regression lines from different regions is a good indication of how complex the relationships are between the mechanical properties of a single species, even from a restricted group of growth areas. A similar set of regression lines is also given in the Gradewood project report for Scots pine, but solely including growth regions of Sweden, and this graph shows only a slight reduction in varying slopes and intercepts.

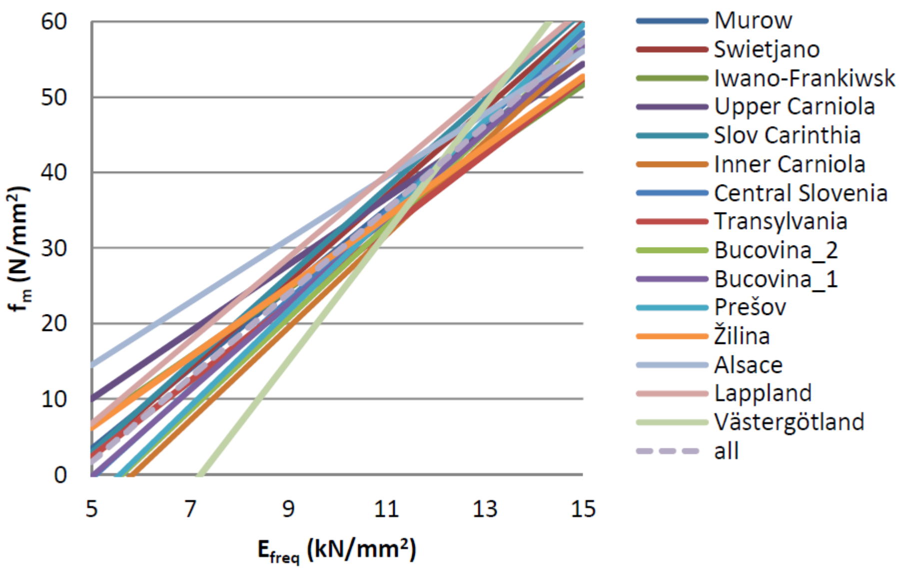

Figure 2.5. Regression lines for spruce for all regions of the Gradewood project (Ranta-Maunus, Denzler and Stapel, 2011, p. 22)

In summary, the strength of the relationship between density and both MoE and MoR is weak to moderate and the strength of the relationship between MoE and MoR is moderate to strong and at least for Norway spruce, this is stable between different growth areas. The strength of the relationship between MoE_{dyn} and static MoE is very strong and shows that MoE_{dyn} can be a useful predictor for static MoE. This is particularly so when measured density is included in the determination of MoE_{dyn} and is less so when a constant density is assumed.

2.4 Brief overview of timber sourcing and use in the UK

The significant numbers and importance of the remaining 18th and 19th century buildings in the building stock of the United Kingdom is apparent during all but the briefest of visits to any town or city. Although the number of buildings remaining from the 18th century is far smaller, it is likely that their historical significance will be correspondingly greater due to their increased age and rarity. The historical nature of the population of in situ structural timber in the UK leads to two issues. Firstly, the make-up of this population needs to be understood before considering any statistical analysis. Secondly, for a practising structural engineer, recognising and dating a building could help in determining the origin, species and quality of its structural timber, commonly used in the wall partitions, floors and roofs.

For centuries, proximity to ports of import has significantly affected costs of domestic and imported construction materials, as overland transport has been so much dearer than transport by sea. This has led to a view held by some structural engineers and surveyors that much timber in the east of Britain is from the Baltic states and Scandinavia and conversely, timber in the west of Britain is from Canada and the USA (Anon, 2008; IStructE, 2010). It is hoped that the information presented below shows that the picture is more complex and that the population of timber in existing buildings in the UK is extensive in more than one way.

In the 17th century, Britain's mercantilist and colonial policies combined with the previous deforestation of Britain to create a critical need for timber for the Royal Navy, the merchant navy and for domestic consumption. A strong navy was essential for control of trade routes which in turn were essential for a strong navy. The nascent industrial revolution of the 18th century led to increased demand for timber for industrial processes, industry and housing. The growth of Britain's population and industry continued throughout the 19th century, thus requiring the importation of nearly all construction timber used, initially, almost wholly from Europe and later, also from North America.

This sub-section presents firstly a very brief description of the natural distribution of the relevant commercial softwood species and secondly it considers the factors that affected their importation and use in the UK during the 18th and 19th centuries: industrial development, settlement, transportation, conflicts and alliances, and the international timber trade.

Four commercially important European softwood species [*Pinus sylvestris* (Scots pine), *Picea abies* (European spruce), *Larix decidua* (European larch) and *Abies alba* (Silver fir)] are presented in Figure 2.6 to illustrate the interrelation between natural distribution, river transportation (blue lines on the map) and importation to Britain. The two dominant softwood species throughout the continent of Europe were and still are *Picea abies* and, particularly, *Pinus sylvestris*.

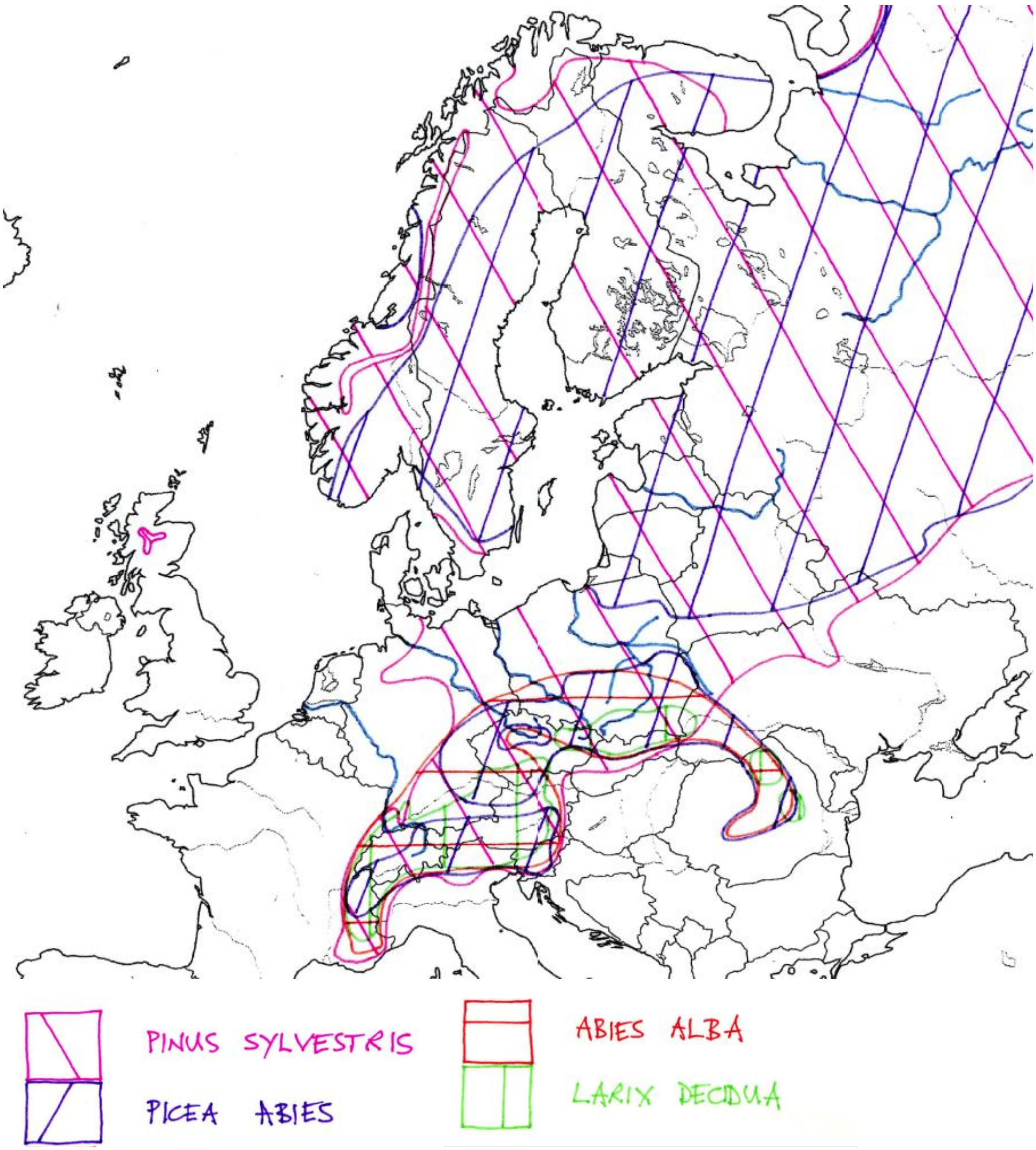

Figure 2.6. Natural distribution of the four key commercial tree species in Europe (EUFORGEN, no date)

Pinus sylvestris is the most widespread species, growing close to all the ports of the Baltic Sea (excluding Denmark) and the White Sea. Additionally, a broad belt of this species extends across Russia almost to its eastern border with China (Critchfield and Little, 1966). To the west, the Rhine river flows through the western edge of its distribution and thus the port of Rotterdam could have shipped this species, which in any case, would be expected to be exported from almost all mainland European ports north of Rotterdam in significant quantities.

Picea abies is naturally distributed throughout Norway, Sweden, Finland, Russia, Belarus, Latvia, Lithuania and Estonia (EUFORGEN, no date); extending along rivers to coasts and close to the ports of shipping such as Memel (Klaipeda, Lithuania), Riga, Archangel and Christiania (Oslo, Norway) which have excellent access to this species. The natural distribution also includes South and East Poland, limited areas of East and South Germany, West and Central Austria, West and Central Czech Republic. Thus, the ports of Danzig, Stettin, Hamburg and Rotterdam may also have shipped this species, despite the distance of its growth areas from the sea.

France, Germany, Austria and Italy all have significant commercial softwood forests that satisfied local and domestic markets which did not extend to the UK to any appreciable degree.

The breadth of commercial species in North America is wider than in Europe and the distributions of just seven of the most historically commercially important softwood species are shown in Figure 2.7. In brief, *Pinus echinata* and *Pinus palustris* are found in the Southern States of America; *Pseudotsuga menziesii* is widespread in the west of North America; *Tsuga heterophylla* has a slightly reduced distribution also in the west of North America; *Pinus strobus* (Eastern white pine) is found in the east of Canada and north-east of America and finally, *Picea glauca* spans the whole of Canada, extending only a little into the north of America.

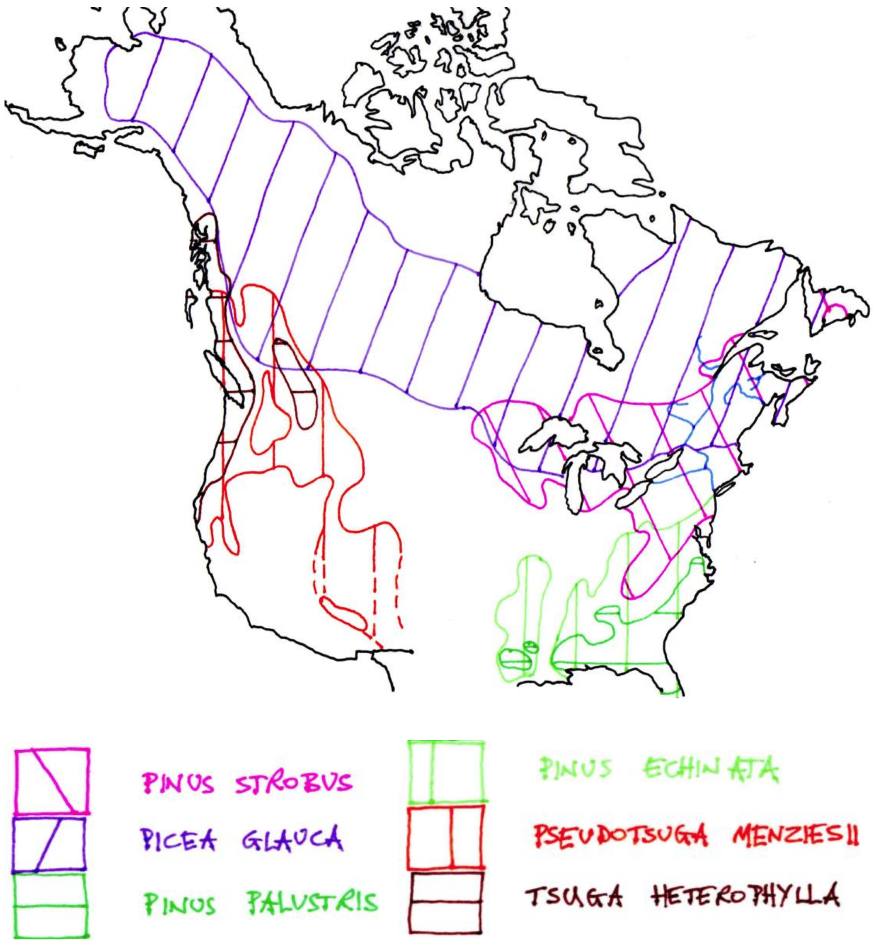

Figure 2.7. Natural distribution of six commercially important (in the 18th and 19th centuries) species of tree in North America (USDA Forest Service, 1990)

At each point in history a builder in the UK would have a choice of species and source limited by the cultural, developmental, economic, and political factors prevalent at that time. These factors determined that during the 17th century, almost all of the deals used in the UK's construction industry were imported from Norway and that during the 19th century, the breadth of timber supply grew and changed to become dominated by North American timber and then returning to a dominance of European timber but extending beyond the Baltic regions to include Northern Russia.

Two events are presented to illustrate the effects that political events have had on the timber trade:

American War of Independence	1775 - 1783
Napoleon's Blockade and UK timber duties	1788 – 1866

Prior to the War of Independence, the provision of masts for the Royal Navy exported from North America was significant and valued by England, despite overall volumes of sawn and hewn timber from this source remaining small throughout the 18th century. An immediate outcome of the loss of the American colonies was the loss of naval mast supplies from New Hampshire and Maine. Such was their importance to the nation, that while the War of Independence was still being fought, alternative sources were being sought from the catchments of the Miramichi and St John rivers in Nova Scotia, British North America (modern day Canada).

To strengthen links with British North America (to prevent its annexation by the newly formed USA and to give it an economic impetus by encouraging its timber trade) HM Government levied timber duties on timber imported into the UK from Europe. This had the added benefit of extending the UK's supply of timber beyond Norway and the Baltic, which was shortly to be blockaded by Napoleon. Thus, the Royal Navy remained supplied during perilous times for the UK and new sources of timber arrived for builders to use.

So, the sources of supply of imported timber varied according to the progress of the various wars of this period and according to the scale of the timber duties which waxed (to a maximum of £3 5s per load in 1819) (House of Commons, page 5, 1835) and waned; finally being removed in 1866 (Potter, 1955).

The graph shown in Figure 2.8 illustrates the estimated relative proportions of timber imported into the UK by region. Throughout the 19th century, demand grew from less than 500 thousand loads of 50 cubic feet to over 2 million loads well before the end of the century, and so, the latter years of the century could be considered more important than the earlier years.

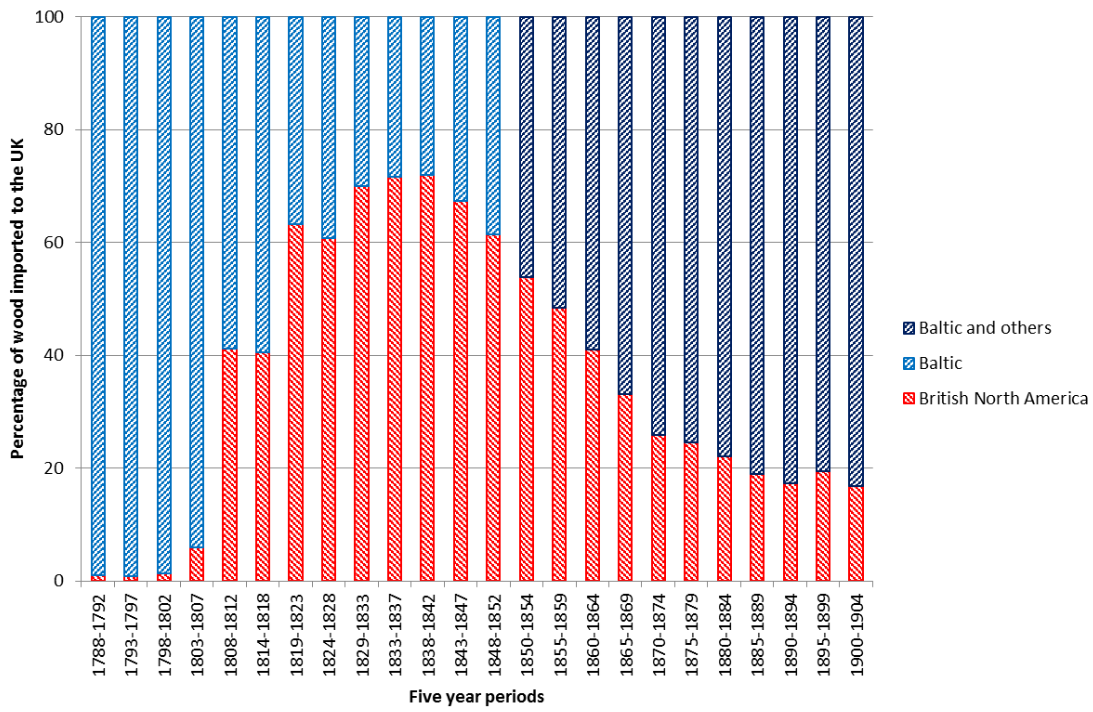

Figure 2.8. Relative percentages of imports of building wood from the Baltic and British North America (Canada).

In Figure 2.8, between 1788-1792 and 1848-1852 the percentages are based on the approximate volumes of imports of deals and square timbers entering the UK. Between 1850-1854 and 1900-1904, the percentages are based on imports of 'building wood' (House of Commons, 1835; Potter, 1955; Lower, 1973) assuming Standard Hundred for deal is 165 cubic feet.

Not only was timber imported into the UK from a variety of regions during the 19th century, but its availability to local builders varied according to the international and national transport networks prevailing (and which changed throughout the century, for instance with the completion of the transcontinental railways in the USA, new regions and species became available). In the UK, Liverpool took more wood from North America than any other British port and around twice as much as London, which by the end of the 19th century was effectively only receiving Baltic timber (Lower, 1973).

As each new region is exploited for the export of timber, first of all the best quality and most profitable trees are felled (particularly for the Naval Mast Trade in the northeast of the US and in the east of Canada), followed by the trees from those regions with convenient access (i.e. internal transportation systems such as rivers) to ports for onward travel. The North American foresters typically felled their forests with no consideration for future regrowth of trees, whereas the Europeans managed their forests to allow the exploitation of replacement stands of trees. The size and age of the trees from managed forests are smaller and younger than those from virgin forests.

Despite this, contemporaneous accounts in the UK describe the timber from North America as typically being second rate in comparison to timber from Europe (House of Commons, 1835). Thus, affecting its likely uses and locations of use. Further compounding the issue of the diversity of the population of in situ timber in the UK is the grading that took place within Europe for at least some of the imported timber. Timber from all sources varies in quality and so can be graded accordingly; for example, Memel and Dantzic timber was rated Crown, Middling, Best Middling and Brack (Vandenabeele, Bertels and Wouters, 2016). Other European sources operated similar but different systems of appearance grading.

Seddon (1889) gives advice on the matter of reading and understanding the bracking or sorting systems used on the continent of Europe and in Canada, which is complicated by the crude markings inscribed or stamped onto timber yet including rich information about quality, volumes of timber, loads, shipping company and port of shipment. Five qualities are described (from best to worst): Crown, First or Best middling, Second or Good middling, Third or Common middling and finally 'short and irregular'. The marks are described as '*often very numerous and perplexing'* (p.119). Different sorting grades and marks are used in different countries and for differently sized timber elements, which adds to the confusion. In Gefle in Sweden, for timber deals to be graded as first quality: '…*Four or five 'knots' only, of the diameter of five-eighths of an inch, are allowable, and these knots must be of the same colour and appearance as the deal itself*…' (Vandenabeele, Bertels and Wouters, 2016, p. 166). This shows that some form of grading based on knots is taking place, even if only appearance grading.

Seddon viewed the process with scepticism: '*There is no absolute uniformity about these quality marks*…' and '…*one shipper's good middling being often nearly equal to another's best middling*' (p.121). In any case, with '…*architects, clerks of works, and* *builders generally, brands upon timbers are looked upon with perfect indifference*.' (p.131). So, Seddon considered that the appearance grading and marking was not understood by architects and builders and so the careful sorting of timber in the timber trade only roughly made its way to construction sites, perhaps through pricing and specifications but not through any particular knowledge held in the construction industry. Donaldson's book of specifications from the 19th century (Donaldson, 1860) bears out this point with no references to the specific appearance grades described above, but instead referring to 'best' and other descriptions.

Table 2.7 shows the price differences between loads of differently graded timber and here, 'short and irregular' is almost half the cost of crown timber from Dantzic and Memel. So, even though the construction industry did not understand the intricacies of the bracking system, they would well understand differences in price, which acts as a proxy for quality.

Table 2.7. Relative value of different kinds of square timber, suitable for building purposes (wholesale prices of timber in 1879) extracted from (Seddon, 1889, p. 125)

	per load of 50 cubic feet.		
Riga	63 shillings	to	67 shillings.
Dantzic and Memel crown	80	,,	90 ,,
,, ,, Best middling	70	,,	80 ,,
,, ,, Good ,,	62	,,	67 ,,
,, ,, Common ,,	52	,,	57 ,,
,, ,, Undersized	52	,,	60 ,,
,, ,, Small, short, and irregular	45	,,	55 ,,
Stettin	53	,,	60 ,,
Swedish, 12 inches square and over	53	,,	55 ,,
,, small, over 9 and under 12 inches square	47	,,	50 ,,
Swedish and Norway balks, 9 inches square and under	32	,,	38 ,,
Quebec yellow pine	60	,,	75 ,,
,, Red pine	50	,,	65 ,,
,, Pitch pine	60	,,	75 ,,

All this is important because any prior grading (through the bracking system, or through specifications or through pricing) will affect the 'quality' of timber used in different structures (compare a prestigious hospital with a slum dwelling). This in turn affects the distribution of the mechanical and physical properties of the population for the predictive models in this study.

Further research is needed to better understand firstly, the application of the appearance grading rules in use, for instance in the 19th century, in the various regions supplying timber to the UK, and secondly, how the various grades finally translated into use in the range of structures built then. A thread can be found through the current European appearance grading code (CEN, 2000), through the previous Nordic grading rules linking to the bracking grades described by Seddon above (FSS, STMY and TTF, 1997; Swedish Wood, 2016) which provides a useful starting point.

To sum up regarding the population of timber used in the construction of the buildings that remain standing today: firstly, this is incredibly varied and is significantly more varied than the populations of timber currently used in the development of visual grading and strength classification codes of practice. For in situ structural timber in the UK:

(i) Timber sources vary across several regions from two different continents with varying forestry practices
(ii) Timber species vary according to the regions which supplied the timber trade
(iii) Timber sources have varied enormously over time, during the 17th, 18th, 19th and 20th centuries (as have the forestry practices of the different regions)
(iv) The 'quality' of timber used in structures of differing levels of prestige will vary significantly in ways that are yet to be fully understood

Secondly, to assess the source and species of timber used in the construction of a particular building that remains standing today, whose origins span over several centuries, is a complex matter and doing this from a desk study, is unlikely to lead to a definitive answer.

Thus, important information for any one structural timber element (such as growth area, forestry practices used, manner of conversion, first growth or second growth, etc.) will not be readily available for any predictive model.

Thirdly, prior grading will have taken place, in ways that currently are not possible to determine and this should be reflected in any predictive model created to estimate timber properties.

2.5 Changes in timber quality over time

2.5.1 The changing quality of the supply of structural timber over time

Controlling the age of harvest is perhaps the quickest and easiest way to control the quality of wood and during the 20th century, economic pressures led to a shortening of rotation ages and a subsequent reduction in the quality of the timber produced due to the associated higher proportions of juvenile wood and knots (Zobel, 1984). These same pressures together with environmental ones, are leading to the consideration of lesser used species of trees (previously ignored) as sources of structural timber (Gil-Moreno, 2018). Once again, this leads to an increase in variation of the structural timber produced.

During the 20th century, improvements in understanding and application of forestry methods and tree selection and breeding have to some degree ameliorated the reduction in quality due to the above factors. Nevertheless, timber being harvested in the 21st Century is second generation growth and its hallmarks are reduced density and lower values of its mechanical properties when compared with the first generation growth timber found in many older buildings and structures (Kasal and Tannert, 2010).

In the previous two centuries, the European forestry industry (exporting to the UK) has expanded, in many small steps, from its Norwegian roots, to include the hinterland of the Baltic Sea, finally extending to include the hinterland of the White Sea and the north coast of Russia. At each step, access to mature forests has provided mature trees with high quality timber. Additionally, the rotation age of the timber harvested from the managed forests declined only slowly over the centuries, thus reducing both the length and quality of the managed timber, but at a much slower pace than has taken place during the 20th century (Hutchison, 2012).

In North America, virgin forests were encountered and plundered, as foresters first felled close to the coast, and then followed rivers inland and finally following the newly built railway lines to allow transportation of logs to sawmills and ports for onwards transmission (Latham, 1957; Lower, 1973). This led to the working out of forests (with the most profitable trees being felled first, followed by the smaller trees of inferior form, and new species would appear on the market from time to time as they became commercially available).

To compound the above, it should be noted that ‘quality’ is a subjective term, often reflecting the cultural understanding and practices of the user of the term. That timber from North America was often described as being of inferior quality when compared to European timber by British carpenters (House of Commons, 1835), is likely to at least partially reflect their own lack of understanding of its characteristics, its strengths and weaknesses.

Thus, the quality of the supply of structural timber to the UK over the previous three centuries has varied due to constant changes of region of supply (on local and global scales), with associated changes of species and forestry practices. These changes have been overlapping and are almost impossible to trace in relation to any particular building or structure. For instance, Scots pine joists encountered in a 19th century building could be from a managed forest in Norway or from a virgin forest in northern Russia.

A caution is worth noting here that contemporaneous values of the properties of timber from past centuries must not be taken at face value. Several issues affect the use of reported values such as seasoning and preparation of test pieces, their method of test, the use of clear wood or structural sized test pieces, size of sample and how representative it is. So, it is unlikely that past reported values of timber properties will be of use to a structural engineer.

2.5.2 Load duration effects

Timber suffers a significant loss of strength over long periods of time, particularly when highly stressed (especially when accompanied by significant changes in temperature and moisture content). Based on the outcomes of several studies, it is seen that “*over several orders of magnitude of rate of loading, strength is approximately an exponential function of rate*” (page 5-38, Forest Products Laboratory, 2010). Thus, mechanical and physical properties obtained from a load test lasting five minutes (100%), would be greater than that obtained from a test lasting 20 years (approximately 80% based on composite results of research on bending, compression and shear).

Bending strength is affected even more significantly than compression and shear, leading to reductions from 100% down to around 60% over ten years in comparison to bending strengths obtained from relatively short term laboratory tests (Wood, 1951). Therefore, due to the need to design buildings to last for several decades, most timber design codes include a factor of around 0.6 to relate long term permanent loads to short term laboratory tests (Hoffmeyer, 1995). This factor equates to predicted bending strengths at the ten year marker.

EC5 adopts a k_{mod} factor to account for the reduction of bending strength due to duration of load. The k_{mod} factor is 0.6 for 'permanent actions' (loads with a duration of ten years or greater) in 'service classes 1 and 2' (temperature of 20°C, relative humidity of surrounding air only exceeding 85% for a few weeks per year) (CEN, 2006).

Structural timber elements spend their entire lives supporting the full dead loads associated with their structures and typically, much shorter periods of time supporting their full dead and live loads (Ross, 2002) as live loads are only fully applied infrequently. Thus, their stress levels in service are typically low, which limits their loss of strength due to load duration. This indicates that the application of the k_{mod} factor is generally conservative in design. However, it would not be possible to increase this factor safely as it is not possible to guarantee the likely low magnitude and duration of live loading applied to a structure over its future working life.

In any case, the 'Madison curve' predictive model based partly on the research of Wood (1951), is based on small clear specimens of a limited number of species, and has since been investigated further using a wider range of species and with structural sized test pieces. The results of these investigations are mixed (Hoffmeyer, 1995; Svensson, 2009) and due to the limited number of tests carried out (due to the difficulty of set up and expense) the predictive models resulting from the research are seen to be tentative at best when applied to actual design situations. Additionally, the duration of load (DoL) tests extend over a relatively short period of time and yet are used to predict the behaviour of timber over much longer periods. This involves extrapolating beyond the timeframe of the laboratory tests, which brings its own risks. Finally, this is also affected adversely by the difficulties in assessing future loads to be applied.

DoL tests are typically based on some form of 'matched pairs' of which one test piece is tested to failure by increasing loads during a short test and its pair is tested to destruction under constant load over a much longer period of time. The disadvantages of this are (i) increased variability due to the matched pairs and (ii) the test results do not help researchers to understand the basic mechanism that causes the DoL phenomenon.

The possibility that load history could reduce bending strength has been investigated, considering a 'gradual damage accumulation' model (Ellingwood, Hendrickson and Murphy, 1988) and other models (Köhler, 2002). These studies find that load history prior to failure is not significant (for instance pulses of snow load on a roof), however, the largest load events have the potential to weaken timber, and particularly, the weakest timber elements (Svensson, 2009).

So, when appraising old timber, a desk study of an existing building should aim to determine any large load events and may ignore the routine loading history of the structure. This is fortunate, because generally, it would be difficult or impossible, for a practising structural engineer to obtain accurate and complete information on the detailed loading history of an in situ structural timber element.

When designing a new timber structure, theoretically, a 'working design life' is chosen by a structural engineer which for the suite of Eurocodes is the '*assumed period for which a structure or part of it is to be used for its intended purpose with anticipated maintenance but without major repair being necessary*' (CEN, 2005) and for most structures, this amounts to 50 years. This design life is far shorter than all of the existing buildings dating from the 18th and 19th centuries and hopefully it will be far shorter than all of the newer buildings of the 20th century and later. However, its length is really a way of determining the probability of certain load events occurring, rather than a way of describing the ageing of the structure.

It is apparent from the age of the housing stock in the UK that 50 years is not an appropriate estimate for the design life of a house. Over 20% of the English housing stock predates 1919 and almost 55% predates 1965 (Ministry of Housing Communities and Local Government, 2020). So, over half of all existing houses in England are currently over 55 years old and over 20% are over 100 years old.

Currently, UK structural engineers use a design life of 50 years (CEN, 2005) with an associated k_{mod} factor of 0.6 (to deal with load duration) for the design of houses which are very likely to have much longer actual lives. The actual life of a house could span hundreds of years and so how does this relate to the chosen value of k_{mod}? Additionally, for an existing house, built over one hundred years ago, but with the potential of remaining for another one hundred years, what factor of k_{mod} should be adopted?

To answer these questions, the relationship between long term bending strength and short term bending strength determined in the laboratory should be looked at a little more closely. This relationship is called the 'stress ratio' by Wood (1951) and this is logarithmically related to the loading duration in hours. Using Wood's original graph of stress ratios, the data in Table 2.8 can be determined, based on a six minute long laboratory test.

Table 2.8. Stress ratios based on Wood's original graph and load durations expressed as log time (hours), with a six minute long laboratory load test as datum

Loading duration	Log (loading duration in hours)	Stress ratio = $\frac{short\ term\ loading\ stress}{long\ term\ loading\ stress}$
6 minutes	0.1	100%
10 years	4.94	62%
11.4 years	5	62%
50 years	5.64	58%
100 years	5.94	56%
114 years	6	56%
200 years	6.24	54%
1140 years	7	48%

It is seen that once a time limit of around 50 years is passed, then the rate of reduction in bending strength lessens quickly, in accordance with the logarithmic expression of load duration. Thus, the stress ratios for 50 years and 100 years differ by only 4%. But the stress ratios for 100 years and 200 years differ by only 2%. These are relatively small differences.

Bearing in mind the imprecision of load estimation, the unlikely extended presence of high live loads and the need to extrapolate beyond the original test data, the size of the k_{mod} factor in new build is seen to be an estimate that roughly but adequately accounts for the load duration affect in structural timber (which, in housing, is likely to have a future life span far greater than its design life span of 50 years). It is reasonable, therefore, to apply the same factor when appraising existing structures, even when their life-span already exceeds the 50 year recommendation in the design code. The proviso for this is that the condition of the structural elements and the structure as a whole is investigated by a structural engineer and not found wanting in any significant way.

With regard to bending deflection, the results of 'duration of load' tests, carried out on small clear specimens, show that, at relatively high stresses, creep deflections increase over time until they equal initial bending deflections (after between six months and a year). Creep deflections, at lower stresses, increase to between 60% and 80% over a similar time frame (Forest Products Laboratory, 2010).

EC5 adopts a k_{def} factor to account for the additional creep deflection following the instantaneous deflection of timber elements. This is applied in a different manner for dead and live loads to reflect the likelihood that the load is more or less likely to be present for the entire life of the structure (CEN, 2006). This approach works adequately for the design of new build and could equally be applied to the appraisal of existing structures, whose existing deformations are easily measured.

2.5.3 Temperature effects

Increases in temperature lead to thermal degradation of wood and tend to reduce the bending strength of timber by up to 25% for a rise from 20°C to 50°C (Forest Products Laboratory, 2010). Some effects are reversible and others are not. Of the little information available on temperature effects, it appears that not only does bending strength reduce as the temperatures increases, but also its variance increases and density decreases (Sinha, Gupta and Nairn, 2010). These effects are complicated by changes to equilibrium moisture content and dimensional shrinkage and, overall, the effects of temperature changes, cycling temperature changes, loading and moisture content are not well documented.

Although in the UK, buildings are not subjected to extremes of temperatures, there is a greater range of temperatures in other countries (e.g. the continent of Europe and the USA). Within a structure, those timber elements located, in for instance “cold roofs” (i.e. roof constructions where the structure lies outside the insulation and so subject to external heating in summer and cooling in winter) will be more susceptible to temperature cycling than others. Additionally, many buildings (over the course of their lifetimes) will have been subject to accidental fires, during which temperatures may have risen enough to affect some timber elements while not rising enough to create visual signs of thermal degradation. These are likely to be local effects but should not be ignored.

Thus, there is the possibility that in any structure, some timber elements may have been subject to temperature cycling over many years or even in some cases subject to greater heating due to an accidental fire. While changes to MoE and density should become apparent in NDT measurements, the estimation of MoR, through a model, based on other measured parameters, may over-estimate the bending strength of temperature degraded timber. This is a topic for further research.

2.5.4 Changes to mechanical and chemical properties of aged wood

It is a commonly held view that structural timber undergoes little or no degradation over extended periods of time as long as its environment is maintained to avoid fungal or insect attack (Yu and Bulll, 2006). Timber durability is assessed and managed on this basis in the Eurocodes, with timber categorised in relation to wood-destroying fungi and attack by insects (CEN, 2016c). That the material itself (and its mechanical and physical properties) may change over time is not considered, however, this is the topic of this sub-section.

The ageing of wood is an unusual topic with little published research possibly due to the limited availability of samples to investigate, the limited knowledge of the history of timber samples and their original condition and mechanical and physical properties.

This is compounded by the variability in the properties of timber and the variety of methods used in the research of aged wood. So, it is not surprising that what is published has mixed conclusions, as found in the 2016 review by Cavalli et al. whose review focusses on the mechanical testing of aged timber and typifies other literature reviews of the subject.

The stiffness of aged timber can be approximately compared to similar new timber of a similar density. Over twenty studies are presented in the review paper by Cavalli *et al*. (2016), which typically show no significant change in MoE; four studies showed a decrease and four showed an increase.

The bending strength of aged timber can be approximately compared to similar new timber of a similar density also. Over eighteen studies are presented in the review paper by Cavalli *et al*. (2016) which typically show a small or no significant change in bending strength; eight studies showed a decrease of bending strength in aged timber and two showed an increase.

The tentative conclusions of the review are that as timber ages, its stiffness remains the same and its bending strength possibly reduces for some species in some circumstances. Several issues are described by Cavalli *et al*. which make it difficult to draw definitive conclusions from the studies included in their review:

(i) Where sample sizes are given, these vary from 9 to 633, with lower numbers being typical (examples given as n = 25, 29, 32, 53, 90, 200). These small numbers are compounded by the variation in the size of test pieces and source locations of samples, together with varying species.

(ii) In some studies reviewed, aged timber was compared with new timber, described as being similar, based on species and density (only approximate matches for density are reported). In other studies, aged timber was compared with new timber based on visual grading categorisation.

(iii) None of the studies were able to be sure of the history of the timber elements in relation to history of loading and moisture content. Additionally, most of the studies made use of salvaged timber, which had undergone demolition/dismantling and it is not known how the possibly extreme stresses that could occur during this process could affect the mechanical properties of timber elements.

Large sample sizes are needed to adequately account for the variability of the mechanical and physical properties of wood. Greater uniformity in the treatment, source location and species of samples is needed to allow different studies to be combined meaningfully. Rough approximations between aged and new timber limit the validity of the research. Without knowledge of the loading history of the aged timber, it is not possible to control for its consequent load duration effects.

The tentative conclusion of Cavalli *et al*. that bending stiffness possibly reduces with age, is not confirmed by Sonderegger *et al*. (2015), either in their literature review or in their limited testing of Norway spruce and silver fir. This is supported by Nilsson and Daniel (1990) who found minimal ageing effects on wood up to 4400 years of age (where no insect and fungal attacks were present). Finally, the literature review of Kranitz *et al*. (2016) confirms that no, or inconsistent, trends are present for the bending strength and stiffness of aged wood.

One effect of ageing that has consistently been found in literature reviews (Sonderegger *et al.*, 2015; Cavalli *et al.*, 2016; Kranitz *et al.*, 2016) is a slight reduction in the impact bending strength of aged wood and its increased brittleness. Interestingly, impact bending strength is the only strength of timber that increases with increasing moisture content (Silvester, 1967) and as is noted below, as timber ages, it becomes less hygroscopic and so, for the same temperature and relative humidity, aged wood has a lower equilibrium moisture content than new wood and this reduces its impact bending strength.

Impact bending strength is a mechanical property that is required of structural timber when it is called on to resist forces applied to it over a very short period of time, for instance, during an earthquake or explosion or vehicle crash. It is not routinely used in the design of timber buildings. However, in relation to those particular circumstances, structural engineers should be aware of its likely limited deterioration in aged wood.

The limited and tentative conclusions regarding the mechanical and physical properties of aged wood are evident regarding the chemical composition of aged wood also

(Kranitz *et al.*, 2016). A tendency for hemicellulose content to reduce within aged wood is contrasted with mixed results regarding ageing effects on crystallinity and the content of cellulose, lignin and extractives. As hemicellulose degrades, the equilibrium moisture content of wood reduces, which in turn can apparently reduce say tensile strength perpendicular to the grain.

Finally, the chemical changes that occur over the lifetime of wood are partly dependent on its environmental conditions (Kranitz *et al.*, 2016) and for instance wood exposed to direct sunlight will undergo UV degradation (Sonderegger *et al.*, 2015) as lignin is particularly sensitive to UV-light. However, this is expected to be superficial only and almost all in situ structural timber in buildings is protected from UV degradation by the building envelope.

Overall, the many changing factors of ageing wood make it difficult to understand and predict its effects. In summary, in the appraisal of aged wood's mechanical and physical properties, no clear evidence has been found to demonstrate deterioration over time of its MoE, MoR or chemical properties. Some reduction to impact bending strength would be expected, which is rarely of interest to a structural engineer. Despite this conclusion, aged wood may have deteriorated, for instance, due to: (i) fungal attack, (ii) insect attack or (iii) mechanical damage. Effects from these causes should be measured by a structural engineer surveying an existing building and accounted for. Typically, the deteriorated wood is measured and discounted and what remains of the cross section of a timber element is used as a basis for structural calculations.

One further point is worth noting in passing regarding the presence of fissures and splits in old timber. From an anecdotal perspective, these appear more common than in new timber and this may be due to larger cross sections of old timber and their changing moisture content over many years. If this is indeed an issue then this will affect the cross grain properties of old timber and the assumptions of EN384 regarding the calculation of secondary properties from primary ones would need reviewing. In any case, as above, fissures detected during a site inspection should be accounted for in any design calculations by a structural engineer.

2.5.5 Physical damage from nails

2.5.5.1 Correlation between nails and mechanical properties

One of the studies of the literature review into the effects of ageing on timber properties, indicated a correlation between the numbers of nail holes measured in reclaimed joists and MoE and MoR. Higher numbers of nail holes were seen to weakly correlate with reducing values of MoE and MoR (Nakajima and Murakami, 2007).

The study used a sample (n=633) of 38mm x 89mm joists, 2340mm long which were assessed and then tested to destruction. Both MoE and MoR were seen to reduce as the number of nail holes (on either the vertical wide face or the horizontal narrow face) increased. Figure 2.10 shows the graph presented in the study for horizontal narrow face nail holes.

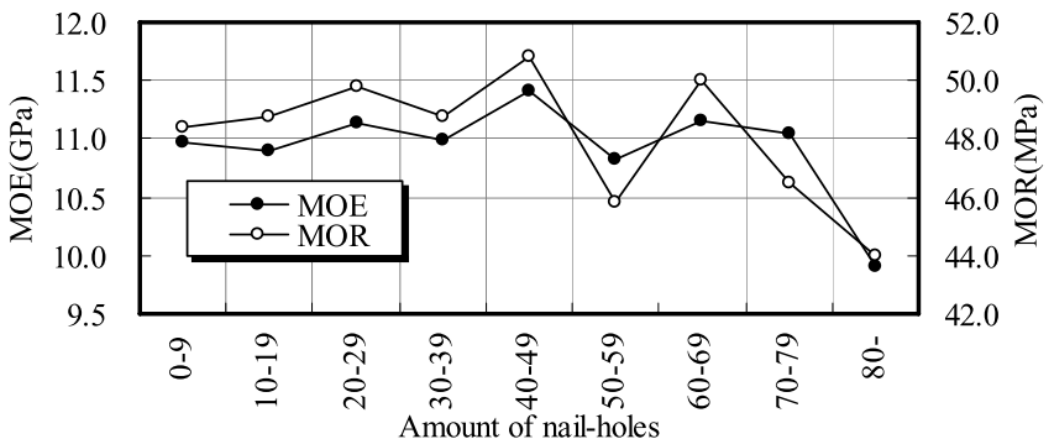

Figure 2.9. Effect of narrow surface nail-holes on the flexural properties of the lumbers. Extract from a study by Nakajima and Murakami (2007, p. 566, Figure 8)

From the data in the journal article, it is calculated that the values of both MoE and MoR reduce by around 10% when the nail count exceeds 70 in the narrow face and 60 in the wide face. This is surprising, as nail damage to the narrow face would be expected to have a greater effect on MoE and MoR than damage to the wide face of joists. A couple of points are worth noting.

The correlation noted between nail hole count and mechanical properties may not be a causal one. The nail hole count may rather be a proxy for the condition of a joist. A nail count of 70 plus is a probable indication that the joist has been used and reused in the past. For comparison, a joist supporting 125mm wide floorboards which are double nailed, would have a total of 16 nails over 1m length in its narrow face. The joists in the study are 2.34m in length and so a nail count of 70 equates to 30 nails over 1m length, i.e. twice as many. Additionally, the wide vertical faces of joists are rarely nailed and so to receive say 60 nails (i.e. 26 nails over 1m length) is unusual and indicates heavy past usage.

Detailed information is not provided in the study which prevents firm conclusions being drawn from it. For example, numbers of test pieces in each of the categories of nail hole counts (e.g. 30-39, 40-49, etc.) are not given in the study and so the results may be influenced by a small number of joists in the extreme category of 80 plus for instance. This naturally leads to a suggestion for future research in Chapter 9 to investigate this 10% reduction in mechanical properties in relation to nail holes.

2.5.5.2 Damage due to nail insertion and removal

The presence of nails is an issue that may significantly affect the mechanical properties of salvaged timber elements and requires some consideration to clarify its effect on in situ structural timber. Firstly, it is understood that for a new building with structural timber elements, it is usual to use nails as fasteners and there are no special allowances for the damage caused by the insertion of nails in the current design codes. So, it is reasonable to assume that an allowance for this (if needed) is included but hidden within the design codes.

Secondly, it should be noted that the damage caused by the insertion of a nail is likely to be much less than the sum total of the damage caused by inserting a nail and then subsequently removing the nail, particularly if the nail is not straight and has rusted.

Thirdly, some nails (particularly the older ones) cause more damage than others. A brief review of the history of nail making and use in construction shows that until the Tudor period, handmade square nails are used and, around 1600, the first rudimentary nail making equipment was built which required much manual intervention to create very similar nails (Nelson, 1968). Nevertheless, this allowed square shaped nails to be made more cheaply. An improved, semi-automated nail making machine was developed at the very start of the 19th century, which cuts nails from a wrought iron sheet, creating rectangular nails. This was finally superseded by fully automated nail making machines developed at the start of the 20th century which created nails from coils of steel wire (Sjögren, 2013). These round, parallel shanked and smooth nails have reduced holding power than the previously used square nails and cause less damage to timber as the square and rectangular nails have sharp and uneven corners that can cut and tear the fibres of wood.

Thus, structures built before the start of the 20th century would be expected to have greater damage for each nail (especially if denailing is carried out) than more modern structures (however, with the ease of nailing using a nail gun, modern structures may suffer from a greater rate of nailing). Additionally, the assumption that current design codes are already adjusted for nail damage may not hold for the rougher, square edged nails of the past.

Bearing in mind all of the above, it is considered that there is a good possibility that denailing old timber could damage the wood and reduce its strength and stiffness and so this is of particular interest when creating a model for salvaged structural timber. For in situ structural timber, on the balance of information held presently, it appears that nailing alone is not an issue, but that the general condition of timber elements (their past use and reuse, mechanical damage etc.) is an issue that should be accounted for in a predictive model. This is also something that should be investigated further.

2.5.6 Biological damage

Moisture is perhaps the most important factor in the service life of wood, affecting its dimensional stability, adhesives and connections, progressive deflections and biological attack (Carll and Wiedenhoeft, 2009). Moisture contents of 20% and greater are a strong indicator of performance problems with wood due to biological attack. The lifetime of many structures includes periods of poor maintenance and neglect, which, in the UK, are strong indicators of damp ingress. Poor detailing or construction can also lead to moisture ingress. Thus, biological damage is a common occurrence in timber structures.

It is essential to identify biological damage and to map its extent. The effect of the damage may be, for example, to reduce the cross sectional area of the timber element that can be relied upon and/or it may be to reduce the density of the wood. An analysis of the environmental conditions is needed to determine the nature and cause of the damage and then to put in place effective remedial measures (Cruz *et al.*, 2015).

The biological deterioration of timber is not part of this study but, where present, it is likely to affect the measurement of MoE_{dyn}. It is not known how changes in MoE_{dyn} relate to possible changes of the bending strength of joists suffering from biological attack. However, Yang *et al* (2003) found that the strong correlation between MoE_{dyn} and MoE remained constant for Tasmanian oak (*Eucalyptus obliqua*) (n=167) for specimens of both clear wood and decayed wood. This is a positive indication for MoE. Additionally, Ross et al (1997) investigated the relationships between stress wave transmission and the compressive strength of decayed wood and developed models with '*excellent'* agreement. Thus, it is hopeful that further investigation will lead to useful links between NDT and the properties of decayed wood (as well as for clear wood).

2.6 Summary of factors affecting the properties of wood

Before considering what should be included in the appraisal of an existing timber structure (what should be measured and how), it is worthwhile to summarise the various factors that affect the mechanical and physical properties of wood. In this sub-section, these factors are summarised and listed to make clear their variety and extent.

2.6.1 Anatomical and chemical composition of wood

The mechanical and physical properties of wood are partly determined by its anatomy and its chemical composition:

1. The structure and composition of the cells and the cell walls
2. Thickness of cell walls
3. Microfibril angle in each of the three layers of the cell walls
4. Relative proportions of cellulose, hemicellulose and lignin

2.6.2 Species, trees, stands, growth areas, juvenile and mature wood

The mechanical and physical properties of wood are partly determined by the environment and the forestry and commercial practices each tree is subjected to:

1. Species of tree
2. Forestry practices and site conditions
3. Location of a tree within a stand
4. Location of a stand of trees within a forest
5. Location of a forest within a growth area
6. The relative proportions of juvenile and mature wood
7. Processing of wood into structural timber elements
8. Method of conversion/sawing of wood
9. Method of seasoning/kiln drying
10. Appearance grading of timber in the supply chain
11. Ad hoc grading of timber by buyer for construction company
12. Ad hoc grading of timber by carpenter constructing with the timber element

2.6.3 In service past life of structural timber elements

The mechanical and physical properties of in situ structural timber are partly determined by the timber's environment in use and its service life:

1. Exposure to sunlight
2. Moisture content in service (relative humidity of surroundings, free flow of air, contact with moist or wet materials, protection)
3. Cyclical changes in moisture content that can exacerbate the effects of duration of load and creep
4. Cyclical loading and possible temporary overloading
5. Duration of load effect
6. Temperature effects
7. Possible dynamic loading or impact loading
8. Creep deflection
9. In service damage (e.g. drilling holes and cutting notches for services, fixing (e.g. nails) to the wood and removing fixings from the wood)
10. Natural ageing (bringing about changes in the chemical composition and moisture content)
11. Treatment of wood by chemicals and their long term effects
12. Fungal and insect attack leading from environmental conditions of service
13. Environmental conditions such as road salts on bridges, chlorine in swimming pools and other industrial processes

2.6.4 In service future life of structural timber elements

The future mechanical performance of in situ structural timber is partly determined by its future environment in use and its future service life. Any structural appraisal must include a safe estimate of the same factors listed in the above sub-sections to ensure the structural adequacy and durability of the structure in the future.

2.7 Current methods of appraisal of in situ structural timber

Existing structures may be considered safe when (i) inspection reveals no undue damage or deterioration, (ii) the structural system is understood and is shown to be adequate, (iii) deterioration and maintenance are managed to ensure durability and (iv) no load changes are anticipated or are accounted for in the structural assessment (ISO, 2010).

This thesis concentrates on just one part of (ii) the understanding of the structural system and demonstrating its adequacy. Although the other steps outlined above lie outside the scope of this thesis, they are still clearly essential in the appraisal of existing structures. In order to demonstrate the adequacy of a structural system, the strength and stiffness of its elements must be known. This sub-section focusses on how these properties are currently estimated.

2.7.1 BS4978 and CP112 in the UK

There is widespread agreement within the UK regarding the best way to assess the mechanical and physical properties of in situ structural timber elements (CIRIA, 1994; Ross, 2002; Yeomans, 2003; Williams, 2006; Reynolds and Holland, 2008; J. R. Williams, 2009; The Institution of Structural Engineers, 2010; Williams, 2015) and this is broadly to make use of the visual grading code CP112 along with the exercise of engineering judgement. A sensible set of approaches is outlined by Ross (2002) and is described below.

Four approaches to the strength assessment of in situ timber are proposed. Firstly, the ‘hundred years rule’ states that if the structure has successfully withstood all applied loads for a long period of time (one hundred years is suggested as providing a return period covering 95% of wind and snow loads) then it is likely to continue to do so, with some provisos (applied loading must not increase, the structure can be seen to be stable and repairs are made to any obvious defects).

Secondly, and following on from the hundred year rule, the permissible bending stresses shown in Table 2.9 can be assumed. Note that these are permissible stresses and so are not directly compatible with the Eurocodes. Some conversions are suggested in the literature, but their basis is uncertain.

Table 2.9. Three approaches to obtaining design bending stresses of in situ timber elements based on Ross (2002)

Approach	Permissible bending stress (N/mm^2)	Notes
2	<5	All members without gross defects Lower stresses can simply be based on an assumption of GS grade timber using BS4978 (BSI, 1996) Design/checking then must be carried out in accordance with the related permissible stress design code BS5268 (BSI, 1997) Only if timber elements are calculated to be overstressed using this basic approach should the next approach be taken in an attempt to obtain a higher permissible bending stress.
3	5 - 10	Higher stresses can be used for timber elements, which have at least three of their sides accessible, having visually graded members to the rules of CP112 (BSI, 1971). The same permissible stress design code (CP112) should be used for design/checking. Only if timber elements are calculated to be overstressed using this visual grading approach should the next approach be taken in an attempt to obtain a higher permissible bending stress.
4	10 - 20	Load tests may prove stresses in this region and beyond, but with reducing chances of success. Care must be taken in converting the results of short term load tests to longer term permissible stresses for in situ timber.

Thus, for permissible design stresses using Approach 3 in Table 2.9 the species (or species group) of timber members must be known as well as their provenance. Additionally, those timbers visually graded using the rules in CP112 are typically required to have at least three of their sides visible. The rules governing knots in CP112 are preferred to those in BS4978 as the former are based on the visual appearance of knots on the surfaces of the timber, whereas the latter are based on the cross sectional area of knots within timber members and it is only possible to project these when all four faces of the timber are visible; this is rarely the case.

Despite the more relaxed requirements of CP112 over BS4978, the former code still actually requires all four sides and at least one end of each timber element to be visible to allow grading to take place. Ross's (and other source's) recommendation that only three faces are required (no mention of seeing either end) is not in accordance with the code and no explanation has been found explaining this relaxation which effectively ignores one face of each timber element and ignores rate of growth (which can only practicably be found by examining one end of a timber element, apart from those joists which have been quarter sawn and the engineer can be sure that they are viewing an exposed radial surface).

Finally, in Approach 4, load testing can be used to prove higher strengths in timber members. This needs careful planning and execution and consideration of how short term load tests can be used to provide long term permissible stresses.

It should be noted that Approach 2, detailed by Ross, is extended by TRADA, to include other visual grading codes from the continent such as the Scandinavian code INSTA142. This has a couple of advantages: (i) the design stresses determined from the visual grading of the in situ timbers are directly related to the current suite of Eurocodes and (ii) higher strength classifications can be obtained such as C30, whereas the UK visual grading code BS4978 can never lead to strength classifications greater than C24 (O'Leary, 2020).

That the third approach is inappropriate, inaccurate, and imprecise is discussed in Chapter 1 and it makes no difference whether UK or other country's visual grading codes are used in conjunction with strength classifications (or stress grades as they are referred to in CP112).

Ross makes no mention of laboratory or non-destructive testing, or the combining of results of visual assessment and other testing. However, both of these first two approaches are suggested by TRADA who have combined in situ visual assessment with destructive laboratory testing successfully to derive moderately increased permissible stresses for in situ timber elements (Williams, 2015). TRADA have also tentatively proposed the use of ultrasound non-destructive testing to be used in situ in combination with visual inspection to assess the strength of timber elements (Williams, 2009). No further evidence of TRADA's suggested ad hoc approach was found in the literature review and no suggestion is made by TRADA on how the results of the NDT should be combined with the visual inspection of timber elements in order to obtain mechanical or physical properties that accord with the Eurocodes.

This thesis investigates the combining of non-destructive in situ testing with the measurement of visual characteristics in order to estimate the mechanical properties of timber elements, similar to the approach that TRADA tentatively proposes.

2.7.2 Strength Grading Protocol in the USA

In the USA, a strength grading protocol for in situ timber was produced for the Association for Preservation Technology International and the National Center for Preservation Technology and Training (Anthony, Dugan and Anthony, 2009) . In this document the background to visual grading of new and in situ timber is discussed and a Microsoft Access document is provided that allows simplified visual grading to be carried out. The chief aim of this is to allow a general structural engineer to make use of current grading rules (of the USA) to inform her assessment of the mechanical and physical properties of in situ timber in relation to design.

In order to use this system, the species of wood is needed and it is recommended that samples of the in situ timber are taken and sent to a laboratory for analysis. Only five species of wood are included in the protocol. Next, as the American visual grading system uses different limits for knot sizes etc according to the cross sectional dimensions of a piece of timber, the dimensions of the timber element must be recorded. This is followed by measurements of knots and slope of grain (Anthony, Dugan and Anthony, 2009) .

The grading protocol uses a simple interface to allow the structural engineer to obtain a visual grading category that relates to the American current suite of timber design codes produced by ASTM International. The chief benefit of the grading protocol is the provision of a simplified interface between the structural engineer surveying structural timber on site and the complex set of visual grading standards that are used in the USA. The chief drawback of this approach is that it is inappropriate, inaccurate, and imprecise for all the same reasons as the UK's approach is all these things (which are discussed in Chapter 1).

The appropriateness of using visual grading codes in the assessment of the mechanical and physical properties of in situ timber is particularly pertinent to the aim of this study. Although this is discussed (Cruz *et al.*, 2015) by professionals in the field, no systematic alternative methodology has yet been proposed to substitute the current inappropriate methodology.

2.7.3 UNI11119

In 2004 the national standards agency in Italy published a code of practice whose full title is "*Cultural heritage; Wooden artefacts; Load-bearing structures - On site inspections for the diagnosis of timber members"* (UNI, 2004). Once again, this is an attempt to provide a method for the appraisal of the mechanical and physical properties of in situ timber which can be based solely on visual grading. For each of seven species (including three hardwood species), three grading categories are given (based on visual grading) together with a reject category. In fact, this code allows grading to be based on: (i) solely visual grading, (ii) unspecified in situ non-destructive testing and (iii) a combination of the former.

The visual grading categories are determined from measurements of wane, cracks and shakes, single knots and knot groups, slope of grain for radial sections and slope of grain for tangential sections. Rate of growth is not required.

Values of stresses are given in Table 3 of the code, which are described in Note 2 of the table as follows (using Google Translate): "*The values reported in Table 3 are taken from the text of Structural Engineering Wood by William Jordan where they remained unchanged in subsequent editions (first edition 1946 - the fifth edition 1999)".* It is not clear how these values should be used in either permissible stress or limit state design. They do not appear compatible with the current version of the Eurocodes. Additionally, they are likely to relate to testing carried out on small clear specimens (as opposed to structural sized ones) and on samples drawn from a relatively small time period (in the 1920s, 1930s and early 1940s).

The chief benefit of this approach is that structural engineers are given clear, national guidance in a format that links with other national codes of practice such as UNI11035-1 and UNI11035-2. Once again, the chief drawback of this approach is that it is inappropriate, inaccurate, and imprecise for all the same reasons as the UK's approach is all these things (which are discussed in Chapter 1). One further drawback relates to the use of values of mechanical and physical properties taken from a 1946 publication.

Due to the many changes in sampling, testing and statistically analysing mechanical and physical properties which have taken place since then, it is unlikely that the values in UNI11119 harmonise well with the current suite of Eurocodes.

However, an equation has been proposed to translate the permissible stresses of UNI11119 to characteristic values that are compatible with the Eurocodes:

$$\sigma = f_k \frac{k_{mod}}{1.5\,\gamma_M} \tag{2.1}$$

k_{mod} is the modification factor for moisture content and duration of load, γ_M is the partial factor for materials, σ is the permissible stress given in UNI11119, and f_k is the characteristic bending strength (compatible with the Eurocodes) (Piazza and Riggio, 2008).

UNI11119 appears to be popular on the continent of Europe for the assessment of the mechanical and physical properties of in situ timber, based on its use in several of the papers presented in the 2019 SHATIS international conference on the assessment of timber structures (SHATIS, 2019). Unfortunately, this does not mean that its results are accurate, appropriate or precise, as discussed in Chapter 1.

2.7.4 SIA269

In 2011, in Switzerland, a suite of codes was released, intended to assist in the structural assessment of existing buildings. As well as dealing with important matters such as additional loading, fatigue, accidental actions, durability, etc. the codes propose a semi-probabilistic approach to determining the mechanical and physical properties of in situ structural elements (Brühwiler *et al.*, 2012). Specific distributions are assumed for various actions and resistances which allow assumed characteristic strengths and stiffnesses to be 'updated' when new information is included in a model (SIA, 2011a).

Part 5 of the suite of codes (SIA, 2011b) deals specifically with timber structures and requires statistically updating prior information on material properties, making use of visual inspection results and non-destructive or semi-destructive testing (or possibly both in combination). This is a far from straightforward process and in the 2019 SHATIS international conference on the assessment of timber structures, although several papers were presented using UNI11119, none made use of SIA269 in the assessment of an existing structure (SHATIS, 2019).

2.7.5 EN17121

The scope of the new code of practice is the on-site structural assessment of heritage load-bearing timber structures (CEN, 2019b). As it deals with 'heritage' structures, its aim is to assist in ensuring their continuing safe use. A guiding principle for the survey, assessment and subsequent repair or strengthening is 'minimum intervention', which justifies greater spending on the survey and assessment of the structure. The code emphasises the documentation and understanding of the history of the structure and its contexts; the importance of this wider understanding is at the heart of Sub-section 2.4.

The guidelines allow for limited (minimum but sufficient) sampling, where required and in accordance with EN16085 (CEN, 2012a), typically for species identification or assessment of mechanical and physical properties.

The guidelines recognise the conservative nature of the loads specified in EN1990 (BSI, 2002b; CEN, 2005) and suggests possible reductions: *"…if uncertainties about load history and material properties can be reduced, other combinations of actions may be considered providing suitable safety level is guaranteed"* (CEN, 2019b), without explaining how these reduction should be calculated. It also suggests that the normal serviceability limits of EN1995 could be relaxed, allowing greater deflections and vibrations.

Where fungal or insect attack is noted, then the effective/residual cross section of a timber element shall be determined (with a recommended safety margin) and used in any structural calculations. A binary approach of treating wood as either full strength or zero strength is proposed and caution is recommended as reductions in strength and stiffness up to 10% possibly occurring due to fungal decay, even before decay becomes visible to the naked eye. Additionally, even with modest weight losses of 5 – 10%, the accompanying reduction in mechanical and physical properties can be as much as 80% (Kasal and Tannert, 2010).

It is recognised that it is not generally possible to measure the strength and stiffness of timber elements in situ, but, where necessary for the structural analysis, they should be 'estimated'. On site visual strength grading and the use of strength grades are recommended. "*Timber members should be visually graded according to visual strength grading standard complying with the nature, dimension and position of the strength reducing characteristics listed in EN14081-1:2016, Annex A*" (CEN, 2019b). This is to allow the determination of characteristic values of mechanical and physical properties that can be used in accordance with EN1995 (the timber design code). Measurements of knots, SoG, fissures and RoG are required and it is recommended that RoG is measured by resistance drilling or coring in a perfectly radial direction, which is more easily said than done. The presence of wane can be ignored as a visual grading parameter but should be considered when determining the cross sectional size of the timber element. The use of a national visual grading code is recommended; adapted as required by a specialist. Finally, it is noted that the use of the strength classes of EN338 will most probably result in a conservative assessment.

However, in the general introduction to the detailed survey, the aim of the survey is given as determining the strength grade or '*strength values'* (Section 5.2, page 15). This is a significant departure from solely requiring strength grading, and the adoption of *strength values* should allow a structural engineer to make use of estimates of individual mechanical and physical properties which are higher than the values of a single strength grade, which may be limited by one particularly low characteristic value (of MoE, MoR or density). This is an important distinction, which (although only mentioning strength) can be interpreted to allow all three mechanical and physical properties to be determined individually, and as characteristic values, rather than as a group.

Clause 5.6.4 offers the option for the structural engineer to use one or more non-destructive methods as 'supplementary tests', where measurements can be shown to clearly correlate with the strength of the timber. Thus, it is the intention that visual grading forms the basis of the assessment of mechanical and physical properties but that this can be extended or refined through NDT.

It should be noted that the '*Guidelines for On-Site Assessment of Historic Timber Structures'* (Cruz *et al.*, 2015) which acts as the basis for the structure and content of EN17121 also suggests strength grades or strength values, and noting that the use of strength classes of EN338 would lead to a *'(very) conservative assessment'*.

2.7.6 Summary of current methods of appraisal

It is seen that for structural engineers, the current methods of assessing the strength and stiffness of in situ structural timber (UNI11119, US Grading Protocol, Ross and TRADA) classify the timber into a small number of combined strength and stiffness classes based on visual grading rules for new timber. The TRADA process allows some adjustment in strength assessment following testing.

It is not possible to be sure of the basis of the existing strength grading standards due to the lack of published guidance. Additionally, their appropriateness for assessing historical in situ timber is doubted as, firstly, old timbers are likely to be from a different era of forestry, with different growth conditions, the timber may be typified by close grained, dense timber, though not necessarily of high strength or stiffness. Thus, the relationships between grading indicators and timber properties that hold for modern timbers may not hold for old timbers due to these important differences. Secondly, old timbers may be of differing section size and shape when compared with modern timber elements (as modern construction has rationalised the general arrangement of structural timber and its sizes), thus structural sized specimens used to create the modern standards are likely to be smaller than old timber elements (and if small clear specimens were used, they will be even smaller than the old timber elements) (Arriaga, Esteban and Relea, 2005).

As is discussed in Chapter 1, in many instances, the adequacy of a timber structure will be borderline, and so an accurate estimate of its strength and stiffness is crucial. Thus, a small number of strength classes is inadequate. So, current methods are inadequate for the task.

2.7.7 Issues around applying the Eurocodes to in situ timber

It must be borne in mind that the Eurocodes have been written for the design of new structures. Thus, although most of their content is entirely appropriate for the structural appraisal of existing structures, there is some that is not. This topic is a current one, as the Eurocodes are currently under revision and it is hoped that they will incorporate useful additional clauses dealing with existing structures.

Additionally, the European Commission has ambitions to significantly improve the circular economy of Europe, reducing waste and creating a market for the second use of building materials (European Commission, 2020). The Construction Products Regulations (CPR) are a tool to achieve this and when applied well, the additional information available, thanks to these regulations will help with the appraisal of existing structures. In the meantime, it is worthwhile pointing out some relevant issues.

A structural appraisal carried out in accordance with the Eurocodes will also include safe estimates of future loading applied to the structure along with the application of factors of safety applied to the loads. These load factors of safety have been developed to relate to the design stage of a construction project and relate to the variability of loading applied to a structure over its expected life span. This includes a factor of $\gamma_G = 1.35$ for permanent actions (CEN, 2005) which cannot be known for certain at the onset of a project but which can be calculated accurately for an existing structure. This 35% increase in loading is significant and while justifiable at design stage (before anything has been built) is inappropriate for existing structures.

Additionally, a further load factor of $\gamma_Q = 1.5$ is applied for variable actions which are determined from tables in the Eurocodes. In the UK, the assessment of variable actions is based on Eurocode 1 and the associated National Annex (CEN, 2009; BSI, 2019). For many years, the excessive magnitude of these loadings has been questioned by the industry and particularly in relation to existing buildings (English Heritage, 1994). More recently, the scale of the loadings has come into question in relation to over design and sustainability (Orr, 2018).

Additionally, at design stage a materials factor of safety must be applied to incorporate some allowance for specified elements being supplied at minimum size but within tolerance. The Eurocode tolerance for a timber joist specified to be 47mm x 150mm allows the supply of 46mm x 148mm joist (CEN, 2013b). The smaller joist has an elastic modulus 5% lower than the larger and a second moment of area 6% lower than the larger. Thus, materials factors of safety include an allowance for tolerances which exist at design stage but which do not exist at the time of a structural appraisal of an existing structure.

Bearing in mind the borderline nature of many existing structures, these examples of over design (built into the Eurocodes) have a significant impact on structural calculations being able to demonstrate structural adequacy. Although beyond the scope of this study, the recalibration of design loading and associated factors of safety should be carried out for the specific case of structural appraisal of existing structures. This is recommended in the section on suggested future work. Until this happens, engineering judgement is required to apply these factors wholly, partially or not at all.

2.8 Conclusions

The variability of wood's mechanical and physical properties is partly explained by its complex natural structure and the range of factors influencing its growth, conversion to structural timber and its in service history. The variability of in situ structural timber in the UK is compounded by the extended time period (four centuries) over which many species have been imported, from many growing regions in Europe and North America. Current methods of appraisal based on visual grading followed by strength classification are inadequate and a new approach is needed that is flexible and that links directly with the Eurocodes.

In the next chapter, the background for the development of new methods of structural appraisal is presented, considering the minor species data set, the many measurements that are carried out and the statistical basis for the development of predictive models.

Chapter 3 Materials, methods and statistical background

3.1 Introduction to the chapter

This chapter is broadly divided into two parts. Firstly, the outline methodology for the entire study is presented, to make clear the processes followed and the analyses carried out. Secondly, the statistical background to those analyses is described.

The statistical background firstly, covers the statistical basis of the Eurocodes and the methods used to translate the grades based on visual grading codes into strength classes. Secondly, the methods of statistical analysis that are used in this study to derive predictive models for the mechanical and physical properties of in situ timber are discussed. Additional factors affecting the predictive models are also discussed in Chapter 7.

3.2 Materials and methods

The main sample of timber joists used in this study is a sample of convenience, created and tested as part of the work carried out by David Gil-Moreno in undertaking his thesis titled "*Potential of noble fir, Norway spruce, western red cedar and western hemlock grown for timber*" (2018). The purpose of this work was to investigate the potential contribution of four minor species to the timber industry of the UK and the thesis contains information on the manner in which the sample of timber joists was created and the structural sized timber joists were cut, seasoned, prepared, measured and tested.

This work was carried out in the spring and summer of 2015 and it focussed on the growth and mechanical and physical properties of four minor species noble fir (*Abies procera*), western hemlock (*Tsuga heterophylla*), Norway spruce (*Picea abies*) and western red cedar (*Thuja plicata*), grown in Scotland, England and Wales. The author shared the work of plotting the knots of the test pieces before they were tested both non-destructively (acoustic resonance testing for dynamic MoE) and destructively in four point bending.

Smaller samples of each of the four species were then salvaged from the destructive testing and were visually assessed, with measurements of slope of grain and ring width being recorded by the author. Finally, from the western hemlock specimens, micro clear specimens were extracted; the acoustic resonance and density of these were measured and then each micro clear specimen was tested to destruction in three point bending, again by the author.

The trees from which joists were cut, ranged in age from 30 to 78 years and were from five sites in the North, Middle and South of Britain. The test pieces are nominally 50mm x 100mm x 3.1m long. Following the use of a bark to bark cutting pattern each test piece was labelled from the pith outwards, to allow its location relative to the pith of the log to be recorded.

The second sample of Scottish grown Sitka spruce (n=60) which is used to partly verify the predictive models was made available from the Strategic Integrated Research Project which was a collaboration between Edinburgh Napier University, Glasgow University and Forest Research (Moore *et al.*, 2009). The laboratory testing was carried out at Edinburgh Napier University after photographs were taken of each face of each nominally 50mm x 100mm timber joists. Knot dimensions and locations from the photographs were converted to a spreadsheet of data using image processing software. All of this work was carried out several years before this study. For this study, the data from the image processing was interpreted and knot measures determined. Next, the sample was visually graded using INSTA142. It should be noted that at the time of testing, each joist was centrally positioned in the test rig (otherwise set up in the same way as for the minor species joists). This differs from current practice of first finding the worst defect of a joist and then arranging this to be in the centre of the test span (where bending moments are greatest). The minor species joists were tested in this way (i.e. current practice).

3.2.1 Measurement of test pieces

The test pieces were conditioned in a standard environment (20°C and 65% relative humidity) and then their longitudinal resonance frequency was measured (together with the overall density of each joist) and knots were measured prior to testing to destruction.

In preparation for the edgewise bending destructive testing, the ‘critical section’ was visually estimated and arranged in the test rig in accordance with EN384, which requires that the critical zone is located at mid-span, but that critical features (such as edge knots) are randomly located at top or bottom of the joist.

Knots greater than 5mm diameter (within the 500mm long gauge length section of the joist) were measured and recorded using the Microtec Web Knot Calculator v2.2 (Microtec, Italy). The transverse dimension of each knot was measured together with its minimum diameter and its transverse and longitudinal position within the joist. Knots were recorded on each of the four faces of each joist, together with the location of the pith.

The 527 joists were tested to destruction in four point bending in accordance with EN384 and results were adjusted accordingly. After testing each joist to destruction, a small density sample (approximately 50mm in length) was cut from the broken joist; measured, weighed, dried and weighed again to confirm its moisture content and density. On completion of the destructive testing, the RoG and SoG of a total of 317 of the 527 joists were measured and recorded.

Measuring test pieces in accordance with the Eurocodes (for instance, measuring a small block of clear wood to determine the density of a piece of wood) is just one of several ways of carrying out these measurements (for instance, weighing and measuring an entire joist to determine its global density, including knots etc.). Additionally, the interpretation of these results can be done in different ways (for instance, there are many statistical measures other than the mean of MoE or the 0.05 quantile of MoR and their 50% two sided lower confidence limits). In this study, the methods of measuring and processing given in the Eurocodes are followed to allow results to link to structural design using the Eurocodes. As such, there is no discussion of the underlying philosophies of the methods used in the Eurocodes.

Adopting this approach aligns this research better with other research carried out in Europe and reduces one source of variability in the relationships between properties and features (by measuring them in a common way). This is not to say that some of the current approaches of the Eurocodes (in relation to in situ timber) could not be improved. On the contrary, a number of approaches are questioned in this thesis. Firstly, for instance, for regression models with large sample sizes, the determination of the 50% two sided lower confidence limit below an estimate adds little value to the process of finding characteristic values. Secondly, none of the current statistical requirements of the Eurocodes address the important issue of selection bias that is discussed in Chapter 7 (this is not surprising as the Eurocodes were not written to address this issue).

3.2.2 Determination of characteristic values

The process of determining characteristic values is begun by the testing of the structural sized joists under reference conditions and in accordance with the Eurocode's testing standard EN408 (CEN, 2012b). It next requires some adjustments to reference conditions and these are discussed below. Finally, characteristic values are determined in accordance with several sections of the suite of codes of practice.

3.2.2.1 Reference conditions adjustments for bending strength (MoR)

Volume and stress distribution effects are accounted for twice in the Eurocodes. The same reference depth of 150mm is specified in both the design code EN1995 and the material code EN384. So, for example, the MoR values, obtained from testing nominally 100mm deep joists, must be reduced through adjustment to a reference depth of 150mm (CEN, 2018b) and then at a later stage, during the design of 100mm deep joists, the design values of the joists would be increased through adjustment to a reference depth of 150mm (CEN, 2006). The two equations used in adjustment for depth cancel each other out.

It was therefore decided that in calculating characteristic values of MoR, the depth adjustment would be carried out for joists but that when comparing visual grading predictions with actual test results, the depth adjustment would be ignored.

From EN384, for typically dense softwood joists, Equation 4 gives

$$k_h = Min\begin{cases}\left(\frac{150}{h}\right)^{0.2} \\ 1.3\end{cases} \tag{3.1}$$

For joists with nominal vertical height $h = 100mm$, this gives $k_h = 1.084$. This is an almost 10% change in value.

3.2.2.2 Reference conditions adjustments for density and moisture content

Density and moisture content were determined in accordance with EN408 and EN13183-1 (CEN, 2003a) using the oven dry method on samples cut close to the bending failure position. Both density and bending strength values were adjusted to the reference 12% moisture content required in EN384.

3.2.2.3 Reference conditions adjustments for modulus of elasticity, MoE

The local bending stiffness, $E_{m,local}$ was measured during the testing but is not directly used in the analysis as it is based on only the short 500mm length of each test piece located in between the two load application points, and therefore more susceptible to local random effects for individual pieces. The shear free modulus of elasticity based on the global MoE is considered to give a better overall representation of the MoE of the joist in bending in a normal situation in use. Shear free MoE values were calculated for each species based on linear regression of measured local and global MoE, and the creation of a bespoke equation to replace Equation (7) from EN384 (Ridley-Ellis, 2011). The coefficients of this equation are given in Table 3.1 (with units of MoE being kN/mm^2).

$$MoE_{shearfree} = m \times MoE_{global} + c \tag{3.2}$$

Table 3.1. Coefficients for the calculation of $MoE_{shearfree}$

Species	Slope m	Intercept (kN/mm^2) c
Noble fir	1.169	-1.111
Western hemlock	1.194	-1.499
Norway spruce	1.198	-1.481
Western red cedar	1.210	0.899

3.2.2.4 Practicalities of applying clauses from the codes in determining characteristic values

The staged process of determining characteristic values is described in Chapter 4. In accordance with EN14358 (CEN, 2016a), the characteristic values for MoR and density are the 5-percentile values for each visual category of joists and the characteristic values for MoE is the mean value for each visual category of joists. The 5-percentile values of MoR and density may be calculated parametrically, assuming a lognormal distribution for MoR (if appropriate) and a normal distribution for density. Thus, a choice must be made as to the preferred method.

The process of obtaining strength classes based on laboratory testing is summarised as follows:

1. Test to destruction 527 test pieces (EN408)
2. Adjust test values to reference values (EN384)
3. Adjust MoR test values to account for k_h and k_l (EN384)
4. Determine 5 percentile values of MoR and density (EN14358)
5. Determine mean value of MoE (EN14358)
6. Determine characteristic values (EN384)

The methods given in Section 3.2 of EN14358 are adopted to find the 5-percentile MoR values at a confidence level of $\alpha = 0.75\%$. Both parametric and non-parametric analyses were carried out (for the grading categories of BS4978 and DIN4074) and after checking the appropriateness of a logarithmically normal distribution, this was used in the parametric calculations. Figure 3.1 shows how the parametric analysis gives higher values than the non-parametric analysis for the categories of BS4978; and this parametric analysis was subsequently adopted in this study for all visual grading codes.

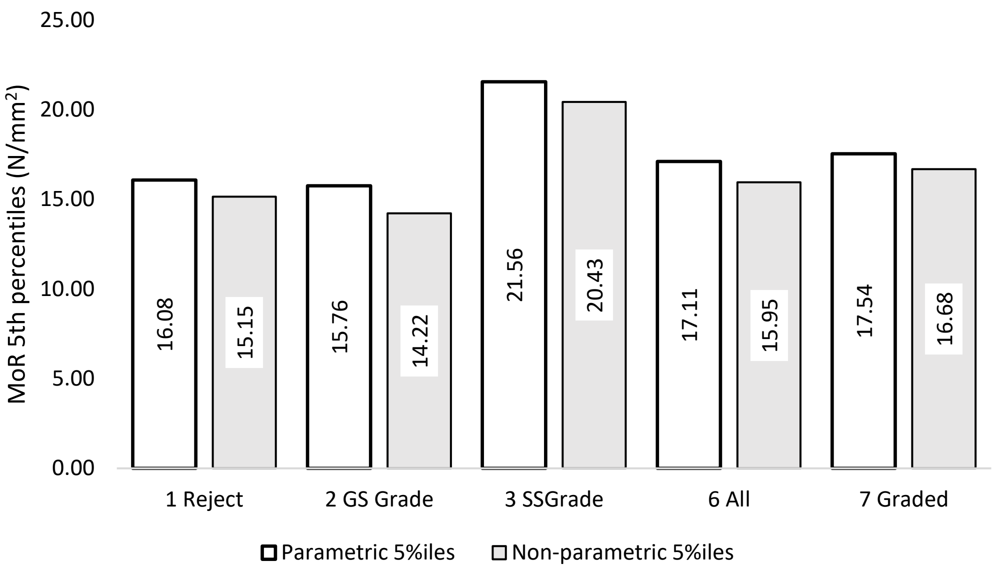

Figure 3.1. Graph comparing parametric and non-parametric MoR 5-percentiles based on BS4978 visual grading of all minor species joists (n=527)

It is assumed in industry, that where alternative methods of analysis are available and, for instance, one is seen to give higher characteristics values, then this would typically be the option chosen. Industry practices and interpretations of the codes of practice, are assumed, where possible, to tend to maximise the yield and strength classifications of batches of timber.

5-percentile values of density were calculated in accordance with EN14358, parametrically and assuming a normal distribution. The value of $k_s(n)$ was determined in the same manner as for MoR. The methods given in Section 3.3 of EN14358 were adopted to find the mean MoE values, assuming a normal distribution of test values. When calculating $k_s(n)$, Formula (18) from EN14358 was used throughout in place of Table 2.

Characteristic values are finally calculated for MoR, density and MoE using the Formulae (11, 12 and 13) of EN384 (CEN, 2018b). Three approaches are possible for a mixed sample such as the 527 joists comprising four minor species. Firstly, all joists could be considered to belong to a single sample of mixed timber and the appropriate values of the factor k_n could be chosen from Table 1 of EN384. Secondly, each species could be considered as a sub-sample of a larger sample, n=527. Thirdly, each species could be considered as a single sample. Each of these three approaches changes both the formulae and the factor k_n and all three approaches were used and compared for joists visually graded to BS4978 and DIN4074. The latter two approaches suffer from very small sample sizes (especially for western red cedar) which render their analyses unreliable and so, in this instance, the first approach was adopted.

3.2.3 Analyses of results and model building

Descriptive statistics that summarise and characterise the minor species sample used in the study are presented in the thesis of David Gil-Moreno (2018). In Chapter 4 of this thesis, the characteristic values of MoE, MoR and density are determined and discussed in relation to visual grading carried out in accordance with three national codes of practice followed by strength classification.

In Chapter 5, the key visual grading parameter of knot measures is investigated in several ways (focussing on single knots, knot groups and knot clusters). Firstly, the methods in the national visual grading codes are discussed and compared and secondly, new methods of measurement are considered. OLS regression is used to investigate the strengths of the relationships between the knot measures and the mechanical properties of the test pieces. While the coefficient of determination is a directly useful measure for mean MoE, there is no similarly useful measure for the 0.05 quantile of MoR. Therefore, the coefficient of determination, r^2, was used for this also, as it still helps to explain the association between the knot measure and MoR. Additionally, other methods such as goodness of fit and ANOVA with nested models are used to understand the strengths of the relationships with the 0.05 quantile.

Finally, a description of the predictive model building for MoE, density and MoR is given in Chapter 8. The methods used differ for each material and are discussed in detail. For MoE, OLS regression is used for the mean and the 50% two sided lower confidence limit below the mean is found using parametric statistics. For MoR and density, quantile regression is used for the 0.05 quantile and the 50% two sided lower confidence limit below the 0.05 quantile is found in a number of ways. The method chosen for the final predictive models uses non-parametric bootstrapping to create linear models and these techniques are explained in greater detail in the chapter and the relevant appendices.

Model building is carried out to create the 'best' model based on the measurements available for the sample of this study and then extended by considering other models which include fewer predictor variables, but whose makeup better reflects the more limited extent of information which may be all that can be gathered from some in situ inspections.

3.3 Statistical background

3.3.1 Introduction and overview

This section is supplemented by further sections in the appendices and together they provide the statistical background for this study. Sample distribution statistics are introduced and an explanation is given as to their use in the determination of material properties in the Eurocodes. Ordinary least squares regression analysis is introduced in relation to predictive models. Quantiles of samples and quantile regression analysis are also introduced and explained in relation to this study. Additionally, some weaknesses of this study relating to its statistical calculations are discussed. The more basic discussions and explanations are to be found in the appendices. This section links with many parts of this thesis but particularly strongly with Chapter 7 which discusses other statistical issues such as selection bias.

To help non-statisticians and practising engineers, a separate guide: "*Guide to statistics in the Eurocodes for timber engineers*" has been written and published as part of this study (it is freely available and can be reached via the link in the appendices). This document is a standalone introduction to sample distribution statistics and their use in visual grading and strength classification in the Eurocodes. The guide explains the steps required to determine the characteristic values of MoE, density and MoR in accordance with the Eurocodes and these steps are followed in this study. The guide covers the following topics:

1 Finding the mean of a sample
2 Finding the confidence interval around the mean of a sample
3 Introduction to the Eurocodes
4 Characteristic value of MoE based on visual grading
5 Characteristic value of density based on visual grading
6 Characteristic value of MoR based on visual grading

The guide presents an explanation of the basics but for clarity, omits discussion of more detailed aspects of the Eurocodes. However, an example is given below of the difficulties of understanding the background and the intent of the Eurocodes in relation to the creation of a predictive model that harmonises with them.

The predictive models created in this study are not based directly on the sample distribution statistics used in the Eurocodes but instead are based on regression models. Ordinary least squares (OLS) regression is used for MoE and quantile regression is used for density and MoR. While several studies are found in the literature review making use of OLS regression, none were found using quantile regression in relation to wood or timber and so this is considered a new approach.

The basis of OLS regression and its assumptions which are presented in the appendices, are discussed in greater detail in relation to model building in Chapter 8. The focus of OLS regression is the mean of a sample, which relates directly to the Eurocodes' method of determination of the characteristic value of mean MoE. However, for density and MoR, the Eurocodes require the lower bound confidence interval around the 0.05 quantile. Thus, for these properties, quantile regression is particularly appropriate. The bootstrapping approaches used in the quantile regression model allow the predictive models of this study to closely mirror the methods required in the Eurocodes and so be in harmony.

Regarding OLS regression, Appendix A covers the following topics:

1 Basis of OLS regression
2 Finding the mean of a conditional distribution
3 Understanding the fit of an OLS regression model
4 Finding the confidence interval around the slope of an OLS regression model
5 Finding the confidence interval around the mean of an OLS regression model
6 Multiple linear regression

Regarding quantile regression, Appendix B covers cover the following topics:

1 Finding the quantile of a sample
2 Finding the confidence interval around a quantile of a sample
3 Introduction to quantile regression
4 Basis of quantile regression
5 Finding the 0.05 quantile of a conditional distribution
6 Finding the confidence interval around the 0.05 quantile of a conditional distribution

The use in the predictive models of the lower confidence limits of OLS and quantile regression was decided upon only after consideration of other statistical techniques and measures and this consideration is presented in a later sub-section.

3.3.2 Quantile regression summary

In general, the chief advantages of quantile regression over OLS regression are (i) the lack of a requirement for assumptions about the distribution of the dependent variable, (ii) the richness of its characterisation of the distribution of the dependent variable, which allows it to describe the relationships between the variables at different quantiles (and not just for the mean) and (iii) the robustness of the approach to outliers. For the specific job of characterising the distribution of the dependent variable MoR in relation to its predictor variables (and in particular the 0.05 quantile of MoR), an important benefit is that the quantile regression model directly focusses on this quantile and provides robust results in a single step (rather than using the OLS regression model to predict the mean and then modifying this, on the basis of assumptions regarding the distribution, to obtain the 0.05 quantile).

Reference should be made to the two indicative graphs in Figure 3.2. For any given value of the independent variable, the linear 0.1 quantile trendline is an estimate of a location below which lie 10% of the dependent variable data points and above which lie 90% of these data points. Despite the data set in the graphs having an increasing variance, the 0.1 quantile trendline based on OLS regression (shown in the left hand graph) is parallel to the mean trendline and does a poor job of locating the actual position of the 0.1 quantile for any given independent variable. In the right hand graph, the 0.1 quantile trendline based on quantile regression diverges from the median trendline and more closely fits the data points around the quantile itself. This is unsurprising as the latter trendline is based directly on these data points.

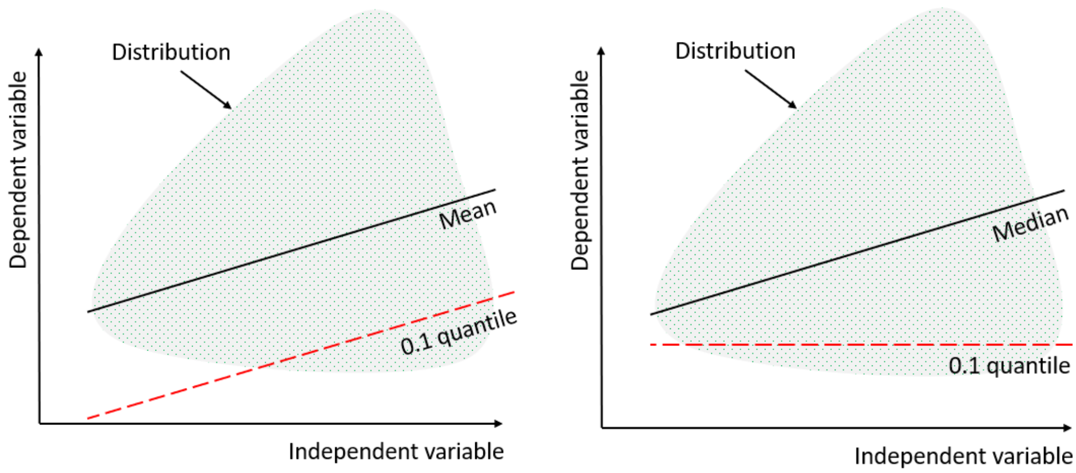

Figure 3.2. Comparison of OLS regression (LHS) and quantile regression (RHS) for the 0.10 quantile

For quantiles close to the median e.g., 0.40 quantile, the OLS regression model is unlikely to differ greatly from the quantile regression model. However, for more extreme quantiles e.g., 0.10 quantile, as shown in Figure 3.2, and for certain distribution shapes, the OLS regression approach does not model the data well and the quantile regression approach is to be preferred. Funnel shaped or triangular shaped distributions are common with variables that are bounded by zero (for instance density cannot be less than zero) and whose values exhibit more variability as they grow larger. As the Eurocodes focus on the 0.05 quantiles of MoR and density, this strengthens the case for the use of quantile regression.

General disadvantages of quantile regression when compared to OLS regression are: (i) that it needs sufficient data, particularly in the tails of the distribution and (ii) it is computationally expensive. So much so that it has only recently become viable as a statistical tool and care must be taken over the methods of quantile regression chosen when applied to large data sets (to avoid excessive computational demand). A further disadvantage to a researcher is that the wealth of software and model building tools available for OLS regression have not yet been developed for quantile regression.

Finally, even though quantile regression can be used to estimate the median, it cannot estimate the mean, which is exactly what OLS regression does. Therefore, for the determination of characteristic values of MoE, it is appropriate to use OLS regression. In summary, where quantiles are required to determine the characteristic values of density and bending strength, for the reasons given above, it is considered that quantile regression is likely to be the most appropriate approach.

3.3.3 Discussion of factors for sub-samples used in the Eurocodes

The majority of the requirements of the Eurocodes are relatively easily understood, however not all are clear. The purpose of this discussion is to illustrate the difficulties of creating a predictive model in harmony with the Eurocodes without being able to be sure of the reasons for and the intent of each of their requirements. The following relates to the factor for sub-sample numbers in the determination of the characteristic value of MoR using EN384.

In the earlier version of EN384 (CEN, 2010) used until the 2016 revision, the characteristic value of $E_{0,mean}$ is calculated in a simple manner, using the weighted average of sub-samples. No additional adjustment is made for number or size of sub-samples.

$$E_{0,mean} = \frac{\sum \bar{E}_j \, n_j}{\sum n_j} \tag{3.3}$$

n_j is the number of specimens in sample j

$\bar{E}_j$ is the mean value of modulus of elasticity for sample j

In the earlier versions of EN384, the number and size of sub-samples in relation to density is not dealt with; however, MoR is dealt with, and in a way that foreshadows the approaches in the 2016 version of EN384.

The following discussion relates to MoR but is considered to be applicable to MoE also. In the earlier versions of EN384, a k_s factor is derived according to the number of sub-samples and the sizes of the sub-samples. This factor is used to reduce the values of the lower confidence limits of MoR, to derive characteristic values. The k_s factor is derived from a range of simulation studies, comparing different statistical approaches (Fewell and Glos, 1988).

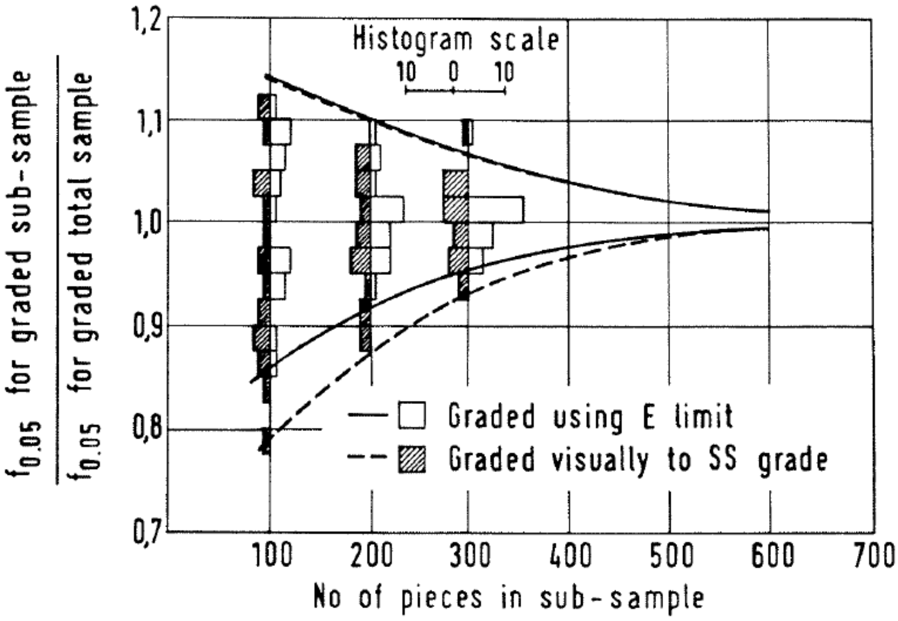

Figure 3.3. Comparison of the lower 5-percentile bending strength values from different sized sub-samples with the 5-percentile value of an entire sample (n=652) (Fewell and Glos, 1988)

Figure 3.3 shows that as the size of the sub-sample increases, so the ratio between bending strengths becomes closer to one. For a sub-sample size of 100, the ratio is approximately bounded between 0.79 and 1.14 illustrating a tendency for 5-percentile values of the sub-samples to be lower than for the entire sample. The k_s values in the graph in Figure 3.4 are based on this and further work comparing different statistical approaches. This graph became the basis of the earlier versions of EN384. Figure 3.4 presents Figure 3, extracted from Fewell and Glos' work (1988) which was incorporated directly into the early versions of EN384.

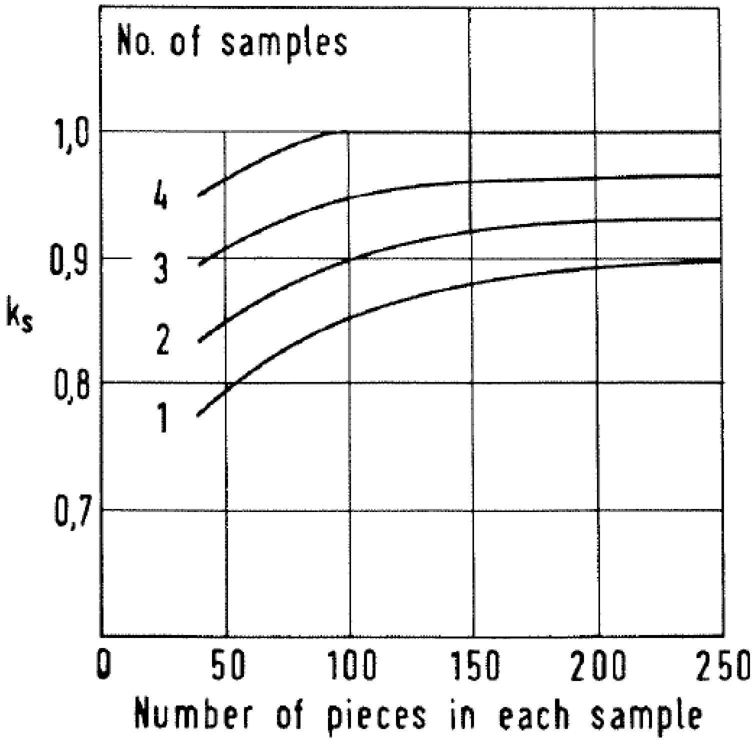

Figure 3.4. Effects of number of samples and their size on factor k_s

So, it is seen that there is a basis for the original version of the code's approach to adjusting MoR, considering both number and size of sub-samples. The latest approach (CEN, 2010) is applied to MoR, MoE and density and only considers the number of sub-samples, ignoring (for this part of the analysis) the size of the sub-samples. For the purposes of this study (when determining characteristic values based on visual grading), the adjustment factor is applied, in accordance with the current version of EN384, but the justification for this remains unclear. In particular, there are doubts as to the need for the additional adjustment when sub-sample sizes are large and a stratified cluster technique is thoughtfully used to create the sub-samples. It appears that grading for a small and tightly defined population is penalised when compared to grading based on a more widely ranging population, requiring more sub-samples. Additionally, the adjustment factor is used with a simple distribution based model and so is not considered to be appropriate for a regression model (other factors are considered more appropriate). Therefore, when creating the predictive model, the adjustment factor is omitted. Reference should also be made to Chapter 7, Factors affecting the model, and in particular to Sub-section 7.3, which discusses the advantages of regression models over simpler distribution based models.

3.3.4 Confidence, prediction and tolerance intervals

As the Eurocodes require characteristic values to be determined from lower confidence limits of distribution models, any predictive regression models created in this study must also include a lower confidence limit, albeit potentially calculated in slightly different ways for different properties. Before settling on the use of confidence limits for the predictive regression models, it is worthwhile to consider the range of limits and intervals that could be considered to be appropriate.

Due to the random variation in samples, statistical intervals can be used to describe the population from which a sample is taken. Three different types of statistical interval are considered here: confidence, prediction and tolerance intervals. Briefly, (i) a confidence interval is a range within which a particular parameter (e.g. mean or standard deviation) is predicted to lie at a certain confidence level, (ii) a prediction interval is typically a range within which a particular value (i.e. one or a small number of data points) is predicted to lie at a certain confidence level and (iii) a tolerance interval is a range within which a particular proportion of the population is predicted to lie. There is some overlap between these intervals as, for instance, a prediction interval could be made for a future sample quantile which is similar to a tolerance interval for a particular proportion.

To illustrate, based on one or more samples of a given species, from one country, the mean bending strength of the entire population of timber joists could be determined with a 95% confidence interval. Thus, the mean value of bending strength of 95% of all future samples from this population (i.e. same species and country, and similarly sized joists, tested in a similar way) should lie within the 95% confidence limits. Similarly, a much wider 95% prediction interval could be determined around the mean which should contain the value of 95% of all future single observations of bending strength. Finally, a 95% two sided tolerance interval could be determined around the mean to contain at least a proportion of say 50% of all future observations of bending strength.

In determining characteristic values of the mechanical and physical properties of timber, EN14358 requires a confidence level of $\alpha = 75\%$, "…*where the confidence level* α *is defined as the probability of which the characteristic value is greater than the* *estimator on the characteristic value*" (CEN, 2016a). Thus, there is only a need to consider the lower limit of say strength or density, and so the focus in this study is on the construction of one sided lower limits.

The $100(1-\alpha)\%$ confidence interval (CI) for a parameter θ refers to the procedure of its calculation rather than to any particular parameter θ or interval calculated from a future sample. The CI refers to many possible independent samples and their own CIs and $100(1-\alpha)\%$ of all these future samples would have CIs that include the parameter θ. In short, if enough future samples were taken, then in $100(1-\alpha)\%$ of these samples, the parameter θ will be found within the CI originally calculated.

Prediction intervals are of most particular use in predicting the performance of just one or perhaps a small number of future observations. A prediction interval (PI) could be made, based on a sample of a population, and with a certain degree of confidence, to contain a future observation from the same population (this may be a single value or a quantile, etc.). So, a $100(1-\alpha)\%$ PI could include the value of a quantile in $100(1-\alpha)\%$ of future cases, sampled from the population.

Prediction intervals may also be calculated to contain the values of all of m future observations or, as a generalisation, to contain the values of at least k of m future observations. These are termed simultaneous prediction intervals and are very similar in nature to the concept of tolerance intervals (TI). In place of at least k of m future observations, it is more usual to require a specified proportion β of future observations to contain certain values and this would lead to a TI. So, a TI contains a specified proportion with a specified confidence level of $100(1-\alpha)\%$.

Based on a sample, tolerance intervals can be calculated, with a certain degree of confidence $100(1-\alpha)\%$, to contain a specified proportion β of a distribution containing a large number of future data points (up to infinity, i.e. conceptually including an entire population). These data points could represent all future in situ timber elements of interest.

Considering the above points, the potential approaches for this study (using the 5 percentile parameter as an example) are:

i. a one sided lower confidence limit for the 5 percentile parameter at a confidence level of $100(1 - 0.25)\%$ i.e. 75% would provide a suitable answer

ii. the one sided lower prediction limit to contain a specified proportion β of a distribution (where $\beta = 75\%$) for the 5 percentile parameter at a confidence level of $100(1 - 0.25)\%$ i.e. 75% would also provide a suitable answer, as long as prediction intervals can be created for parameters as well as values

iii. finally, a one sided lower tolerance limit could be created to contain 95% of all future values of a distribution with a confidence level of 75%.

The middle approach (ii) relies on there being a method of calculating prediction intervals for parameters, which is typically not how prediction intervals are used. Whereas methods for the first and third approaches are readily available. Additionally, the calculation of prediction intervals is particularly sensitive to departures from normality. Therefore, the approaches (i) and (iii) are preferred. So, despite requiring a confidence interval around a predictive regression model, prediction intervals are not considered to be appropriate.

This understanding is confirmed in a standard text book on this topic which notes that a "*…one-sided tolerance bound is equivalent to a one-sided confidence bound on a distribution quantile… More specifically, a one-sided lower 100(1 − α)% confidence bound on the p quantile of a distribution is equivalent to a one-sided lower tolerance bound that one can claim with 100(1 − α)% confidence is exceeded by at least a proportion 1 − p of the distribution*" (p.30, Hahn, Meeker and Escobar, 2017).

Given the more direct approach of deriving a lower confidence limit compared to a lower tolerance limit, this is the approach that is adopted in the predictive models. Additionally, as is discussed later, this approach matches well with a quantile regression approach that also brings significant benefits. The following two sub-sections considers two weaknesses of this study.

3.3.5 Sampling and populations

It is a requirement of the Eurocodes, that sampling is done in a way that ensures that it is representative of the population. The stratified cluster technique recommended by Glos (1985) is presented in EN384. This method divides the population into groups with known differences (e.g. tree size, climate, tree conversion methods) and is the basis of the number and weighted size of sub-samples taken from a population. In practice, the range of a population may vary from a single species in a single region to, for instance, redwood and whitewood together from the whole of Europe (Fewell and Glos, 1988). Thus, in industry, the number and size of samples is not scientifically derived but is based on judgement.

For the test-population in this study, of four minor species from the UK, it would be possible to create sub-samples based on, for example, species or growing region. However, as there are only 527 joists in the total sample, the sub-division of this number creates smaller sub-samples and greater uncertainty when analysed than a single large sample. Refer to Figure 3.5. Thus, the modest sample of joists in this study are treated as sub-samples at times (in relation to the Eurocodes) and at other times all four species are treated as a single sample from the population of the four minor species in the UK (in relation to the building of the predictive models).

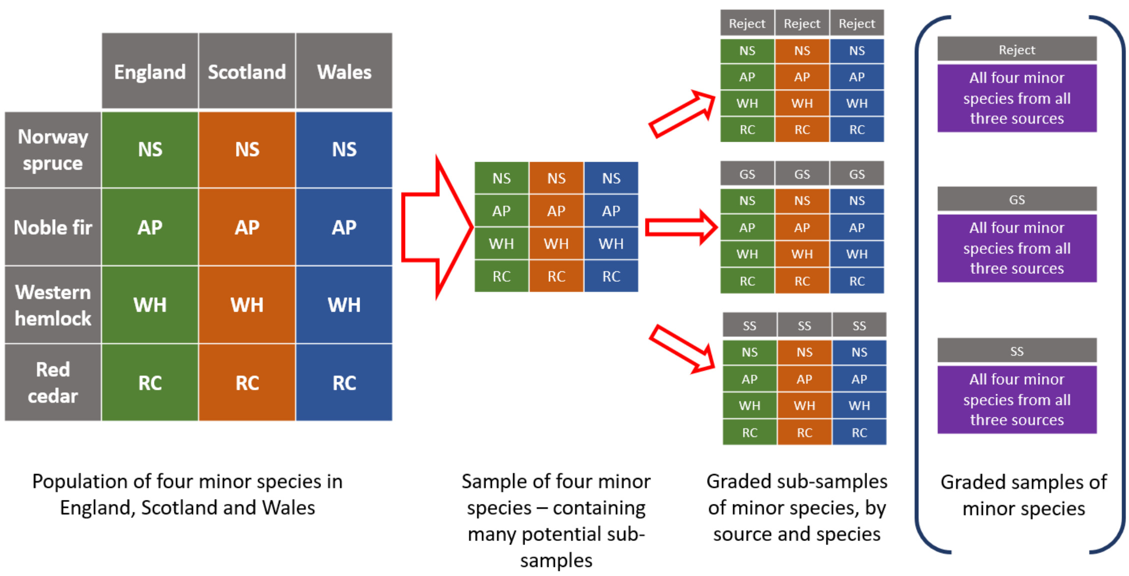

Figure 3.5. Diagrammatic representation of (i) the creation of 36 graded sub-samples and the alternative of (ii) the creation of 3 graded samples. In this diagram the visual grade categories are those of BS4978.

The questions of the adequacy of this sample and how the four minor species relate to the population of in situ timber in the UK are discussed further in Chapter 7.

Sampling requirements in the Eurocodes (CEN, 2010, 2019a) are summarised as:

(i) Test material in samples shall be representative of the population (timber source, sizes and quality)
(ii) Each sample shall be from one source representing one part of the population
(iii) The number of samples shall relate to the number of different parts of the population
(iv) The minimum number of test pieces in a sample shall ideally be 40

Additional guidelines are available for sampling in ISO 3129 (ISO, 2019), however, it is difficult to be prescriptive and it is essential that researchers use their experience and judgement when planning a sampling strategy (Ridley-Ellis, Stapel and Baño, 2016). The most important aspect of any sample is that it represents its population in a valid way. Due to the variability of timber and its growth areas, this is a difficult task. For new timber, the following factors must be balanced:

(i) environmental conditions of the growth areas (e.g. soil composition, depth of soil, exposure to wind and rain)
(ii) composition of the trees to be felled (e.g. their age, species or mix of species, planting densities)
(iii) the expected grade determining properties, including their mean and variance
(iv) the visual grading characteristics and their relationship with the grade determining properties
(v) methods of conversion in local sawmills
(vi) national boundaries and economic issues (which also affect decisions over sample numbers, size(s) and extent(s))

Despite these relatively strict requirements, it is still possible for inappropriate sample data to be used in the grading of new timber. One example of how the mechanical and physical properties of a single species from a single growth area can vary over a relatively short period of time is provided by the Gradewood Project, one of the largest studies of structural timber grading carried out in Europe (Ranta-Maunus, Denzler and Stapel, 2011). This shows, for Norway spruce, grown in Sweden, significant differences in bending strength (mean value and variation) in comparison with the results of earlier studies, which until recently had been used as a basis for strength classification in Sweden.

The justifiably strict requirements for sampling for new timber cannot be applied to existing in situ timber. The population of structural timber present in buildings and structures in the UK is so large and varied that it would not be possible to realistically represent it even in an extended series of samples.

It is noted that difficulties of obtaining adequate samples of tropical hardwood timber have led to the development of a species independent approach, combining destructive test data from many hardwood species with NDT data of new species to create predictive models (Ravenshorst and Van De Kuilen, 2006; Ravenshorst, 2015). It is not known if this approach has been widely adopted in industry yet. The predictive models of this thesis adopt a similar approach in outline. It is essential that the predictive models account for the restricted samples on which they are based and this is discussed in greater detail in Chapter 7.

So, for two reasons, it is decided, in the first instance, to develop species free predictive models to apply to the commonly used softwood timber that makes up the in situ timber in the UK. Firstly, recognising the species of in situ timber is beyond the ability of practising structural engineers and the taking of samples for laboratory analysis is time consuming and costly (in relation to small structural projects). Secondly, the categorization of in situ timber based on species is only one of many refinements that could be made for a series of predictive models (growth area, era of construction, quality of existing building, etc. are just some other refinements) and its effectiveness would be limited, particularly in relation to the larger issues discussed in Chapter 7, such as selection bias. Thus, in this first instance, a species free approach is adopted. However, based on the approaches of this thesis, other researchers could investigate the other potential refinements mentioned above, especially perhaps for the most common species of spruce and pine.

3.3.6 Confounding independent variables

There are many independent variables affecting the mechanical and physical properties of timber joists which can be classed as (i) those that are easily measurable, (ii) those that can be measured with difficulty and (iii) those that cannot be measured. Visual features such as knots, slope of grain, ring width and wane are easily measured.

Microscopic features such as microfibril angle, ratio of earlywood and latewood together with chemical composition e.g., lignin and cellulose content, can be measured with some additional effort. Some factors could potentially be known but are unlikely to be known and include those affecting the trees (from which joists are cut) including their genetics, the nature of the soil where they grew, the weather conditions and climate during their growth and methods of forest management used.

For in situ timber joists, the many factors described above are compounded by other factors which are even more likely to be unknown and which affect the timber joists after their cutting, such as prior grading, cyclic loading and overloading, cyclic changes in moisture content and ageing. These factors could be termed post-use factors and currently, generally relate to the life cycle of a single building or structure within which the timber elements reside. However, with increasing reuse of timber elements and their subsequent transfer from one structure to another, the post-use factors may be affected by several life cycles of very different structures or buildings.

It should be noted that the effects of the post-use factors are not possible to be measured visibly. So, the usual methods of visual grading necessarily exclude the effects of each of the post-use factors. It is only by using NDT/SDT that the effects of the post-use factors could be accounted for, despite it being impossible to directly measure any of these factors. This alone could be enough to convince engineers of the need to include NDT/SDT in the assessment of the mechanical and physical properties of in situ timber elements, and not to rely on visual assessment only.

The NDT measurements of in situ timber elements will not directly address any of the post-use factors but are able to provide data on, for instance, MoE_{dyn}, which it is hoped is a good predictor of for instance, MoE. The relationship between MoE_{dyn} and MoE has been investigated for new timber, many times, and shown to be a consistently strong one (similarly the relationship between MoE_{dyn} and MoR has been shown to be a moderate one also). However, the effects of post-use factors on the relationship between MoE_{dyn} and MoE is not known and so an assumption is made in this study: the effects of the post-use factors on MoE_{dyn} and MoE is similar and proportionate and so the relationship between MoE_{dyn} and MoE remains constant, regardless of the post-use factors.

A similar assumption is made for the relationship between MoE_{dyn} and MoR and any other NDT test results. This assumption needs to be proven in future work and so please refer to Chapter 9.

The many and varied independent variables affecting the mechanical and physical properties of in situ timber elements mean that the issue of confounding variables must be addressed. Additionally, the risk of assuming causality where it is not present must also be borne in mind. The assumed causal relationship between knots and MoR is discussed further in Chapter 5.

Current approaches to visual grading assume an association between the easily measured independent variables (such as knots, SoG, RoG and wane) and the mechanical and physical properties of timber elements. The confounding factors that can only be measured with difficulty or not at all are ignored in the grading. Yet, these factors are both associated with both the easily measured independent variables and the dependent variables (MoE, MoR, density).

Three of the four usual methods of reducing the impact of confounding variables are restriction, statistical manipulation and matching pairs (Thomas, 2020), and are not appropriate for this study. Restriction requires the sample to exclude confounding factors that cannot be measured and to only include confounding factors that can be controlled to be the same for all elements in the study. Statistical manipulation would require the confounding variables to be included in the development of any predictive models which would not be possible for those variables that cannot be measured. For similar reasons, matching pairs are not possible to create.

The fourth method of reducing the impact of confounding variables is randomisation, which for this study, requires a sample size large enough to ensure that its full range of confounding variables is representative of the population at large. While it is considered that this is not practicable to fully achieve, this is the only method open to use in relation to the experimental aspects of this study (other methods are discussed in Chapter 7 in relation to the observational ones) and requires the small sample of this study to be supplemented enormously in the future.

In the meantime, this study creates a model based on test data from 527 joists of four minor species, which are subject to a particular set of confounding variables. The purpose of the model is to estimate parameters of in situ timber elements which are drawn from a wide ranging population (geographical sources, species, age, etc.). So, the model will be biased, i.e., tend to under- or over-estimate parameters due to the unknown and unknowable confounding variables. It is hoped that it is possible to build up a collection of samples over many years to create a more representative data set for in situ timber. At the moment, the bias in this study must be noted and accounted for as best as possible. Reference should be made to Chapter 7, in which methods used in observational studies are discussed in relation to selection bias.

3.4 Conclusions

In this chapter the methods and materials used in the experimental phase of the study are described along with the statistical methods used in their interpretation. A guide to statistics for use by timber engineers is presented. Novel methods of statistically analysing the minor species data set are proposed that lay the basis for the creation of predictive models in Chapter 8. Some of the key difficulties and weaknesses of the statistical methods used in this study are discussed and links made with other chapters where these discussions are extended.

The following chapter makes use of the statistical methods described above (and in the appendices) as part of a discussion of visual grading.

Chapter 4 Visual grading codes

4.1 Introduction to the chapter

In this chapter, visual grading codes are discussed and reviewed in relation to the appraisal of in situ timber elements. Visual grading codes make use of visual features to estimate the mechanical and physical properties of batches of timber. They are also used by structural engineers when appraising the properties of in situ structural timber. So, in building a predictive model for in situ timber, it is important to understand their efficacy, and their strengths and weaknesses.

A separate document ("Technical note on the use of visual grading codes for the appraisal of individual in situ structural timber elements") has been produced which covers the same ground as this chapter in greater detail and so, if more information is required, reference should be made to this.

In this chapter, there is a brief introduction to visual grading together with a short literature review, covering the purpose and development of visual grading together with a review of three national visual grading codes, currently used with the Eurocodes. The three codes are used to visually grade the sample of minor species joists (n=527) and the results are compared with the results of the laboratory testing of the same joists. How well the visual grading codes categorise groups of joists and individual joists in relation to their mechanical and physical properties is considered. Finally, if visual grading codes are not appropriate for the appraisal of in situ timber elements, then are any parts of them potentially useful in building a predictive model for this job? A more detailed discussion of the individual grading features is carried out in the next chapter.

4.2 Literature review

4.2.1 The purpose of visual grading codes

The natural variability of timber is so great that producers have, over time, found it necessary to grade timber as best they can to give some measure of assurance to purchasers and users. Appearance grading is useful for architects and other users and specifiers of wood who require minimum requirements for surface appearance. Strength grading is useful for structural engineers who need to specify structural timber with minimum requirements for mechanical and physical properties. So for instance, for the highest appearance grades (CEN, 2000), no splay or bark ringed knots are permitted regardless of their size as these are considered unsightly. Whereas, for strength grades, knot sizes are limited according to their perceived effects on bending strength and stiffness and so knots of this nature could be acceptable, even for the highest of grades.

The Eurocodes (CEN, 2013a, 2016b, 2019a) define a two stage process of (i) visual grading which places packages of timber elements into visual grading categories (mechanical grading does the same thing) and (ii) strength classification which allots the visual grading categories into strength classes. Structural engineers can then make use of the strengths and stiffnesses in the allotted strength classes when designing buildings and structures (CEN, 2006). Modern strength grading allows a structural engineer to simply specify a strength class (e.g. C24) for structural timber fulfilling a particular purpose and to be sure that the minimum associated values of the mechanical and physical properties of the supplied timber will be provided with a specified level of reliability.

This deceptively simple explanation is reliant on extensive, controlled testing of carefully defined and sampled datasets, the results of which are statistically manipulated, again in a standardised way, to allow the quantification of the properties of timber elements of a particular size, for a particular species from a particular source (CEN, 2010, 2012b, 2016a). It is important to note that the visual grading categories and the strength classes relate to sets of pieces of timber and not to individual pieces of timber. Each strength class is defined by lower bound limits of the key physical and mechanical and physical properties and the strength class to which a batch of timber is allotted is determined by the lowest values of the batch's key physical and mechanical and physical properties. Thus, a batch of timber of low density (but high bending strength and stiffness) joists could only achieve a low strength class (due to their low density).

4.2.2 The development of visual grading codes

Structural engineers and architects have always had to manage the structural quality of timber used in their building projects and, prior to 'strength grading' (as the above process is termed in the Eurocodes), other methods had to be used, some of which are more prescriptive and less flexible. None of which provide accurate estimates of the strength and stiffness of individual pieces of structural timber.

During the 19th century, from experience and trade books on the matter, those working in construction in the UK would have been aware of the relative merits of the various species of softwood available. At this time structural timber can be seen to have been approximately specified on the basis of both species and growth area.

Additionally, some reference to quality (i.e. terms such as ‘best’, ‘free from defects’, and ‘crown’) is also commonly used.

Wood has for a long time been sorted on the basis of its appearance, using commercial or appearance grades such as the Scandinavian system of Unsorted (I, II, III and IV), Fifths and Sixths (Tredwell, 1973), and although this can be an adequate system for joinery, none of the grades are indicators of strength or stiffness. Even so, the appearance grades could have functioned as indicators of the likely strength of a piece of wood. Other European countries adopt similar but different approaches, for instance the Russian equivalent of the above grades would approximately be Unsorted (I, II and III), Fourths and Fifths (Coulson, 2012).

In the UK, early works on carpentry (Nicholson, 1826; Tredgold, 1875) presented the experimental studies of others: limited testing on very small samples of just a few species. As such, due to the variability of timber, these works were and are of very limited value (neither providing useful design information in the 19th century nor historical information on the properties of 19th century timber to structural engineers in this century).

The standardisation of visual grading in the USA began at the start of the 20th century in relation to the needs of the railways (building large scale trestle bridges). Then, during the interwar years in the UK, a programme of testing of small clear specimens began in relation to the needs of the aircraft industry. This industry typically required greater confidence in strength and stiffness values than the construction industry and could afford to use clear wood as its structural members (despite increased costs); hence the use of small clear specimens (Yeomans, 2020).

In the UK, the first codified visual grading code was published in 1952 as the first of four editions of CP112. The first edition of the code provides just two basic stresses for two groups of timber species with limitations placed on knot sizes, slope of grain and rate of growth (BSI, 1952). This edition was based on the results of testing carried out between the wars and of all editions of the code, this one is based on the smallest volume of testing and its limited nature renders it the least attractive to structural engineers. Nevertheless, it forms the basis for the subsequent two revisions published in 1967 (imperial units) and 1971 (unrevised but converted to metric units). Finally, in 1973, Amendment 1265 to the metric version was published, making it the most attractive to structural engineers practising now. This most recent and amended version of CP112 is the one discussed below (unless noted otherwise).

The first edition of the UK's current visual grading code was published in 1973 and this introduced the concept of knot area ratios. Until this point, the effect of knots had been quantified by the ratio of their diameter with the width of the face of the section on which they appear. This new code (BSI, 1973) established the principal of considering the ratio of the projected knot area with the cross sectional area of a piece of timber, in place of the surface knot area. This same method is still in use in the UK (BSI, 2017).

In a similar fashion, other countries in Europe developed their own national strength grading codes. Due to the wide variety of species, dimensions and uses of graded timber, the codes differ from one another and the harmonization of visual grading rules in Europe led to a flexible standard that allows individual countries to develop and use their own grading rules as long as they account for certain minimum requirements in terms of the visible characteristics of wood that must be assessed (Glos, 1995; CEN, 2016a).

It should be noted that each version of each visual grading code has been developed on the basis of testing carried out on specific growth areas and species at a certain time (reflecting the forestry practices of that time). Thus, as growth conditions and growth areas vary over time, then the applicability of older versions of visual grading codes reduces with age. Finally, despite advances in machine grading, much structural timber in Europe continues to be graded visually and based on national standards.

4.2.3 How visual grading is carried out in accordance with the Eurocodes

The process defined by the Eurocodes has been outlined and described by others already (Ridley-Ellis, Stapel and Baño, 2016 , Porteous & Kermani, 2007) and this sub-section merely comments on the most salient aspects of this process. The Eurocodes (which provide a harmonized set of European standards which give common rules for design and common technical specifications for building products) provide only a loose framework within which individual countries can issue their own visual grading standards.

The framework document EN14081-1 (CEN, 2019a) lists requirements for the measurement of strength reducing characteristics such as knots and slope of grain and geometrical, biological and other characteristics. Knots must be measured in accordance with EN1310 (CEN, 1997a); slope of grain must be defined in accordance with EN844-9 (CEN, 1997b) and rate of growth limits are preferred to be given in increments 3mm, 4mm, 6mm, 8mm, 100mm and 15mm. The framework document also requires that either rate of growth (RoG) or density must be included in a visual grading standard (Clause A.1.3 Density and rate of growth) and typically, RoG is used.

The process of strength grading in the UK is summarised below. This contrasts the relatively extensive initial testing process required when a new species or growth area is developed for the first time with the relatively simple strength grading process which can be followed from then on (involving cheap and quick visual grading) for timber elements from known species and growth areas.

INITIAL TESTING: (1) Define species and growth area, (2) Choose sample(s), (3) Visual grading of test pieces in sample, (4) Laboratory testing of test pieces in sample, (5) Using all test pieces in each visual grade, determine the characteristic values of their grade determining properties, (6) Assign strength classes to visual grades.

SUBSEQUENT STRENGTH GRADING: (1) Ensure that species and growth area of timber elements conform to initial testing, (2) Visually grade the timber elements, (3) Determine the strength class of each timber element based on: (i) visual grade, (ii) species and (iii) growth area.

The focus of these two processes on the defined species and growth areas includes an implicit assumption that forestry and sawmilling practices remain constant (along with climate and other growing conditions), which is a reasonable assumption over relatively short periods of time but becomes less reasonable as the period of time stretches from years to become decades (given the research also being done on silviculture and seed selection) and centuries.

The application of current visual grading and strength classification processes to in situ timber would rely on assumptions about the in situ timber regarding: (i) growth areas, (ii) forestry and sawmilling practices at the time of felling trees for timber and (iii) climate and other growing conditions. Given that any one of these factors can significantly affect the mechanical and physical properties of timber (Høibø *et al.*, 2014; Zobel and van Buijtenen, 1989; Stapel and van de Kuilen, 2010), this is an important issue that appears to be currently overlooked.

4.2.4 How well visual grading works in practice

4.2.4.1 New timber

There is little research on the effectiveness of visual grading rules and their application to new timber (Stapel and Van De Kuilen, 2014), and that which was found in this literature review typically focusses on one of three aspects: (i) the economics of grading and the grade boundaries and their effects on yield (and the characteristic values obtained in relation to strength classes) (Almazán *et al.*, 2008; Stapel and Van De Kuilen, 2014) and (ii) new methods of measurement to improve visual or machine grading (Roblot *et al.*, 2010; Lukacevic, Füssl and Eberhardsteiner, 2015; Viguier *et al.*, 2015) and (iii) new methods of combining measurements to improve visual or machine grading (Blass and Frese, 2004; Hanhijarvi, Ranta-Maunus and Turk, 2005; Hanhijarvi and Ranta-Maunus, 2008).

It is worthwhile to report on two studies which focus on the efficacy of current visual grading codes in Europe. Stapel and Van De Kuilen (2014) drew several conclusions following the analysis of over 12 000 timber test pieces which validate the choice of DIN4074, INSTA142 and BS4978 for assessment in this study. These conclusions are summarised as follows:

1. The grading results for DIN4074, INSTA142 and BS4978 are similar and generally meet or nearly meet requirements for characteristic values
2. In most cases, attempting to grade C30 is problematic, leading to inadequate characteristic values
3. Visual grading codes with just two grading categories (plus Reject) such as BS4978 function better than those with more categories

4. The French national visual grading code (AFNOR, 1991) differentiated poorly between C18 and C24 (giving equal yields of each grade with similar characteristic values) and also produced low yields of C30
5. The Swiss national visual grading code (SIA, 2009) had such extreme reject rates that it was not practical to use

Stapel, Denzler and van de Kuilen (2017) reviewed one approach to extend growth areas used in visual grading. Based on Norway spruce from several growth areas of Europe (n=8487), calculated timber properties were found to vary considerably by region. So, pan-European grading areas are considered to be problematic if based solely on visual grading. This is not to say that visual assessment combined with NDT could not work adequately for combined growth areas.

4.2.4.2 In situ timber

There is little research on the effectiveness of visual grading rules and their application to individual in situ timber elements to determine their design strengths and stiffnesses. What has been found in this literature review is generally based on small sample sizes and rarely differentiates between the original purpose of the codes of practice used and the purpose to which they are being put in the research. This is discussed in Chapter 1 where it concludes that the hoped for effectiveness is not investigated in any valid way.

Very few studies have been undertaken assessing the application of visual grading codes to individual timber elements. In one of the very few, Piazza and Riggio (2008) applied two Italian visual grading codes (UNI11035 and UNI11119) to spruce, larch and chestnut with disappointing results. UNI11035 and UNI11119 predicted values of MoR between -31% and +43% different to values obtained from testing.

Finally, as discussed in the Introduction, the superseded code of practice CP112 is commonly used in the UK in the appraisal of in situ structural timber by structural engineers. This old code does not accord with the Eurocodes and is therefore not considered as a potential basis for a future predictive model. However, due to its current widespread use in the UK, it is worthwhile considering its efficacy and this is done in a conference paper (Bather and Ridley-Ellis, 2019), the relevant points of which are briefly covered in this chapter.

4.2.5 Comparison of measures of visual grading codes in Europe

In this sub-section three codes of practice from the UK, Germany and Denmark are considered (BS4978, DIN4074 and INSTA142) (Dansk Standard, 2009; Deutschen Institut für Normung, 2012; BSI, 2017). Each of these three codes of practice have been developed for timber from differing growth areas and hence, even for the same species, different approaches are to be expected. These differences are compounded by different saw milling and construction practices, such that, for instance, one region prefers large square shaped timber joists and another prefers smaller and thinner joists. All three visual grading codes specify limits on the sizes of the timber elements that they are to be used with.

The visual grades from each code of practice have been linked to their relevant strength classes in EN338 using EN1912 and Table 4.1 summarises the differing outcomes of this process. Now, the three most important visual features in visual grading codes are knots, slope of grain (SoG) and rate of growth (RoG) and these also differ. For example, in Figure 4.1, the relative knot sizes for Strength Class C18 are shown to differ significantly.

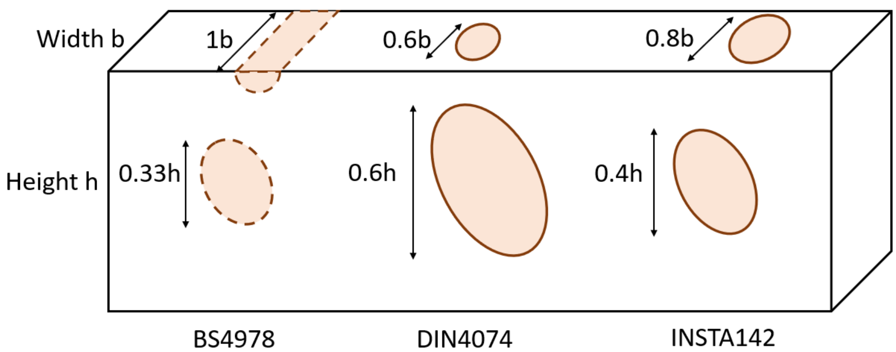

Figure 4.1. Maximum knot sizes relating to Strength Class C18 for BS4978 (derived from knot area ratios), DIN4074 and INSTA142

As the limiting ratios for DIN4074 are the same for both the narrow edge and wide face, in comparison with INSTA142, this code has tighter limits for the edge and looser limits for the face. BS4978 gives knot limits in terms of area ratios rather than dimension ratios. As BS4978 limits both margin and total knot area ratios together, it is not necessary to limit the size of edge knots and this leads to even looser limits for narrow edge knots.

SoG is the three dimensional (3D) deviation of the grain from the longitudinal axis of the timber element, expressed as the deviation in mm over a 100mm length. Two 2D measurements are taken, as shown in Figure 4.2 and then combined to determine the 3D measure.

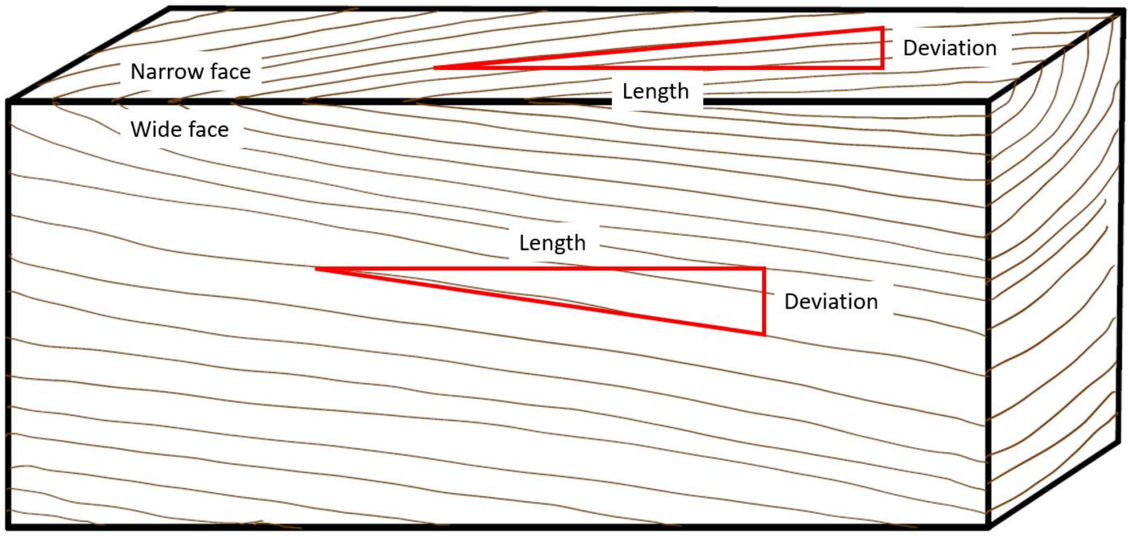

Figure 4.2. The ratios of deviation to length in the narrow and wide faces are combined to determine the 3D slope of grain of the wood

RoG, is given as ring width measured over as long a distance as possible, ideally more than 25mm away from the pith. This measurement is made at one or both ends of a test piece, as shown in Figure 4.3.

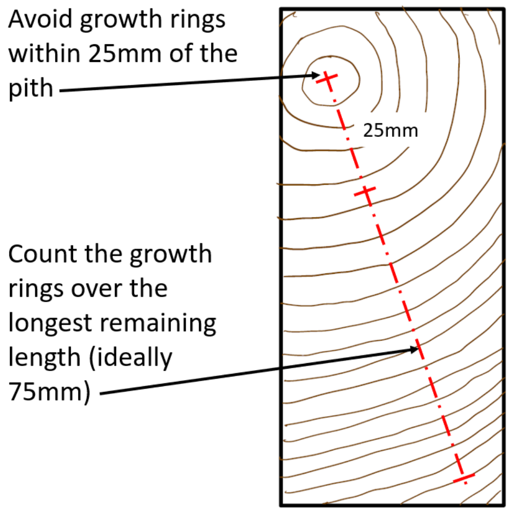

Figure 4.3. The measurement of rate of growth is taken along a radial line, at approximately 90° to the growth rings exposed at each end of a test piece

There is little agreement over limits for SoG, apart from Strength Class C24, for DIN4074 and INSTA142. Whereas, for RoG, there is agreement between the same two codes for both C24 and C30. Of interest is the lack of any limit for Strength Class C14 for INSTA142. The three codes of practice treat knot clusters and knot groups differently and only BS4978 considers knot area ratios. Even the minimum size of knots to be considered in visual grading differs.

All in all, it can be seen that all three visual grading codes are in agreement, with a general pattern of reducing SoG and RoG and knot measures being linked with stronger strength classes, but the detailed limits used to differentiate between strength classes vary. The different ways of measuring knots vary from one code to another and the limits specified for knot measures, SoG and RoG also vary. It is hard to see any patterns in these differences and it is not possible to understand the logic behind them, leading to the conclusion that these differences relate to local forestry and saw milling practices or possibly are of an arbitrary nature.

4.3 Visual grading and strength classification

A four stage process was followed, beginning with the recording of the visual observations (knot measurements, SoG and RoG) of the joists. Secondly the rules of three visual grading codes were applied to each joist and visual grades established; this was also done using CP112 (BSI, 1971). Thirdly, EN1912 (CEN, 2013a) was reviewed in order to choose the most appropriate strength classes to link with the visual grades determined. Finally, EN338 (CEN, 2016b) was used to determine the characteristic values of MoR, MoE and density for the joists graded.

EN1912 links each visual grading category with a strength class only for a limited number of species and growth regions, which it terms 'sources'. From Table 1 and Table 3 from EN1912 the links are estimated for the four minor species investigated and visually graded. Table 3 simply links each species with a reference number used in Table 1. A reduced and summarised version of Table 1 is shown in Table 4.1 below.

If growth areas are to be included in any predictive models for the properties of in situ timber, it would be important to make clear their boundaries. Currently, these are not defined in relation to the growth areas in EN1912. The second Gradewood Project report (Ranta-Maunus, Denzler and Stapel, 2011) proposed to divide the growth areas of Europe based on climate and forestry and sawmilling practices which is theoretically superior to using national boundaries, which however are more convenient.

In relation to this study, DIN4074 relates solely to the CNE region (Central, Northern and Eastern Europe) and INSTA142 generally relates solely to the NNE region (Northern and North Eastern Europe) with just two references to Denmark and Norway. BS4978 relates to the UK, Ireland, USA and Canada (as well as a limited number of other sources with historical timber trading ties with the UK). The minor species were grown in England, Wales and Scotland. Therefore, the references to the UK and Ireland are most directly relevant.

It would be expected that timber from the growing regions of CNE and NNE would be stronger and stiffer than that of the same species grown in the UK. Nevertheless, the strength classes linked to DIN4074 and INSTA142 with their superior growth regions are used with timber from the UK. This is a working estimate and no more and this must be borne in mind when comparing characteristic values of MoR, MoE and density calculated from the laboratory testing of the minor species with the characteristic values obtained from the strength classes in EN338.

The results of the Gradewood Project (Ranta-Maunus, 2009) bear out the expectation that timber properties from differing growth areas differ by differing degrees. The study found that for instance, different grading settings should be developed for Scots pine grown in Germany, France and the UK, whereas the same grading settings could be used for the for Nordic countries. Conversely, for Norway spruce, the same settings could be used throughout Central and Northern Europe (if these included the measurement of stiffness and knot sizes).

Table 4.1 is a much reduced version of Table 1 of EN1912, and only contains the species which have been visually graded and tested in this study. The visual grades in the shaded cells are directly taken from EN1912. All other grades are estimates.

Table 4.1. Summary of the links assumed between visual grades and strength classes in relation to the minor species used in this thesis

Four test species Genus [EN1912 ID No]	C30		C24		C18			C14	
	DIN4074	INSTA142	DIN4074	INSTA142	BS4978	DIN4074	INSTA142	BS4978	INSTA142
Norway spruce (NS) Spruce [22]	S13	T3	S10	T2	SS	S7	T1	GS	T0
Noble fir (AP) Fir [8]	S13	T3	S10	T2	SS	S7	T1	GS	T0
Western hemlock (WH) Hemlock [62]	S13	T3	S10	T2	SS	S7	T1	GS	T0
Western red cedar (RC) Cedar [58]	S13	T3	S10	T2	SS	S7	T1	GS	T0

From Table 1 of EN338 (CEN, 2016b), the characteristic values of MoR, MoE and density can be found and these are presented in a simplified version Table 4.2.

Table 4.2. Characteristic values, extracted from EN338, for MoR, MoE and density

	Class	C14	C18	C24	C30
Bending strength (N/mm^2)	$f_{m,k}$	14	18	24	30
Mean modulus of elasticity in parallel bending (kN/mm^2)	$E_{m,0,mean}$	7	9	11	12
Density (kg/m^3)	ρ_k	290	320	350	380

Following the above strength classification, the characteristic values for each visual grade of the sample were determined through laboratory testing and statistical analysis using EN14358, for comparison.

4.4 Results and discussion

The results of the visual grading for the three visual grading codes BS4978, DIN4074 and INSTA142 are compared with the measured mechanical and physical properties with no adjustments made (for example, for sample size, depth factors, calculation of characteristic values, logarithmic adjustments to the distribution, etc.). Also, the determination of the characteristic values of the mechanical and physical properties of each visual grade is discussed. BS4978 is first discussed in detail to illustrate the approaches taken for all of the visual grading codes.

4.4.1 BS4978

The visual grading of the 527 joists splits them roughly into thirds: Reject, Grade GS and Grade SS. 290 of the 527 joists were graded due to just one visual grading characteristic (i.e. only one visual grading characteristic fell within the limits of the lowest visual grade), most commonly, rate of growth (RoG), closely followed by knot cluster. Of the remaining 237 joists, 41 joists had just two joint grade determining characteristics, while 183 had three or four joint grade determining characteristics. As over half of all joists are graded by just one characteristic, this shows the lack of agreement between the different characteristics.

Of the 184 Reject joists, knot clusters were the sole grade determining feature for 70 joists, RoG for 106 joists and SoG for 1 joist; for the remaining 7 Reject joists, knot clusters and RoG were joint grade determining features.

From the above, knot clusters and RoG are seen to be the two key visual grading characteristics for the sample of joists. RoG is the sole determining visual grading characteristic for over one quarter of the sample of joists and as is discussed elsewhere in this thesis, the measurement of RoG is at best problematic and at worst impracticable for in situ timber. So, the use of BS4978 to visually grade in situ timber would not be considered appropriate for this reason alone. A further compelling reason not to use BS4978 for in situ timber is the difficulty of measuring the knot area ratios of partially covered or inaccessible timber elements. Without access to one or both ends of a timber element and all four faces, the determination of knot area ratios is near impossible. Even when these circumstances prevail the process is convoluted, as is illustrated by Annex A of the code itself.

The importance of knot clusters (grade determining characteristic for 363 joists) compared to single knots (grade determining characteristic for 196 joists) is an indication that (at least for BS4978 and for this sample) knot clusters affect grading outcomes almost twice as strongly as single knots. SoG is the sole grade determining characteristic for only 14 joists and as such affects grading outcomes least of all.

It is useful to understand how well the visual grading to BS4978 manages to differentiate between joists in relation to bending strength, stiffness and density. Broadly, it is seen from Figure 4.4 that there is significant overlap between the visual grades of BS4978 and that some of the weakest joists are graded as GS and SS. Nevertheless, the Grade SS data points are generally towards the top right quadrant of the graph leaving the Grade GS and Reject points intermingled towards the bottom left quadrant of the graph. This suggests some useful differentiation by visual grading for the stronger and stiffer joists but less so for the weaker ones. So, as knot clusters and RoG are the most common grade determining features, they appear to be effective to differentiate higher quality timber but not for lower quality timber.

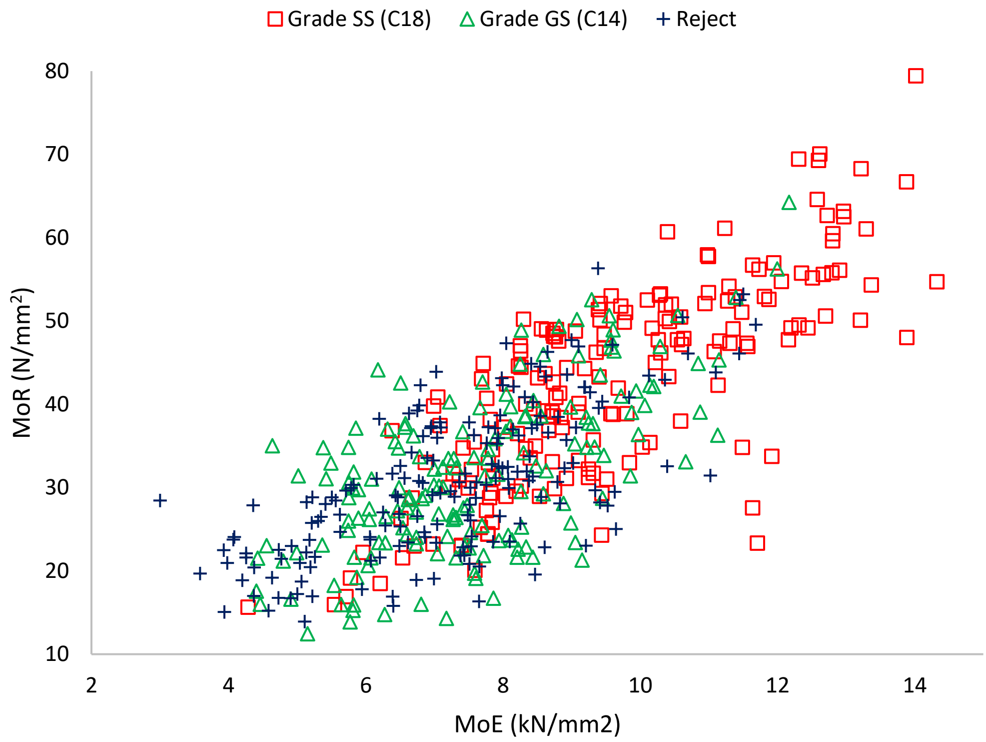

Figure 4.4. Graph comparing MoR and MoE for all joists visually graded using BS498

ANOVA and t tests were carried out to investigate the differences between the MoR values in each of the visual grades determined using BS4978. The output of a t test is a P-value which answers the question: what is the probability that the observed difference in means between two groups is as large as it is observed to be? Thus, a low P-value indicates a greater likelihood that two groups have significantly different means and so can be considered to be from different populations. Whereas high P-values indicate that two groups may be from the same population. An analysis of variance (ANOVA) test is used where more than two groups are to be compared and (similar to the t test) determines how different are the means from different samples. Its output is an F value or F statistic which is the ratio of two variances: the variation between sample means / variation within the samples. The greater the variation between the sample means, relative to the variation within the samples, then the larger the F statistic and the greater the probability that the null hypothesis (of no difference between the means of different samples) should be rejected.

The F value (33.3) of the single factor ANOVA test is significantly higher than the F-crit value (2.38) which indicates that there are significant differences between the grades.

Two sample t tests (assuming unequal variances) were subsequently carried out to compare the MoR values between grades. Two tailed P-values are given in Table 4.3 which show that the means of the two different grades are significantly different, but that the means of the Reject category and Grade GS are not significantly different.

Table 4.3. Two tailed P-values for MoR values of groups based on BS4978 visual grades

Groups	P-value
Reject and GS Grade	0.350
GS Grade and SS Grade	1.58×10^{-18}
Reject and Graded	2.2×10^{-12}
All and Graded	0.005
Reject and All	1.99×10^{-7}

Table 4.3 indicates that although the visual grading rules of BS4978 appear to differentiate the bending strengths of the stronger joists to some degree, the rules do not do this for the weaker joists. Joists allotted to a visual grading category are termed “Graded” (i.e. not Reject).

The same exercises for MoE show a similar pattern with differentiation between Grade SS and both Grade GS and Reject but a lack of differentiation between Reject and Grade GS. For density, its scatter plot with MoR showed much intermingling of data points of differing grades but the ANOVA and t tests show some differentiation between mean values of all grades.

Although the sample size is inadequate to carry out a grading of the minor species, the characteristic values of the mechanical and physical properties can be calculated for the groups of timber graded using BS4978. These values are presented in

Table 4.4 and the shaded cells indicate characteristic values below those required in EN338.

Table 4.4. Characteristic values based on BS4978

	Reject	Grade GS C14	Grade SS C18	All	Graded
f_k (N/mm^2)	11.3	11.0	15.1	12.0	12.3
$E_{0,mean}$ (kN/mm^2)	6.65	6.95	8.83	7.52	7.96
Density (kg/m^3)	311	320	333	325	322

For density, each grade of the graded timber attains the characteristic values of the corresponding strength classes. For MoE, the characteristic values are borderline adequate. For MoR, the characteristic values are too low by around 3 N/mm^2. The performance of BS4978 is summarised below:

1. It sorts the stronger and stiffer joists into groups with similar mechanical and physical properties relatively well but fails to usefully sort the lower quality joists.
2. The code of practice is impractical for use with in situ timber elements due to (i) the use of RoG and (ii) the use of knot area ratios; neither of which can be practicably measured in situ.
3. Knot clusters and RoG are the most important visual grading measures and SoG is the least.

4.4.2 DIN4074 and INSTA142

The same processes were applied to the sample using the visual grading codes DIN4074 and INSTA142 and similar outcomes were obtained. Scatter plots based on MoE, MoR and density show much overlapping of data points from different visual grades. As expected, for both codes of practice intended for growth areas different to the UK, none of the graded timber attains its characteristic values.

For DIN4074, the two sample t tests (assuming unequal variances) showed that the MoR means of the different grades are significantly different, but that the MoR means of the Reject category and Grade S7 are not significantly different. For MoE, there are significant differences between the MoE means of each grade and Reject apart from Grades S7 and S10. The differentiation of the Reject Grade for MoE is much clearer than for MoR. Mean density increases with each increase in visual grading category, however, with only weak differentiation.

The performance of DIN4074 is summarised below:

1. It sorts the stronger and stiffer joists into groups with similar mechanical and physical properties relatively well but fails to usefully sort the lower quality joists for MoR.
2. The code of practice is impractical for use with in situ timber elements due to the use of RoG. However, this is a particularly simple visual grading code to apply to new timber.
3. RoG is the most important visual grading measure and SoG is the least. Single knots are used with simple knot measures (without knot groups or knot clusters).

For INSTA142, the two sample t tests show that the MoR means of the different grades are significantly different, but that neither the MoR means of the T2 and T3 Grades, nor All and Graded, are significantly different.

For density, there are no significant differences between mean density values of any of the grades, with the possible exception of T0 and T1 Grade. For MoE, there are no significant differences for Reject with T0 and for T2 with T3. The performance of INSTA142 is summarised below:

1. Perhaps due to its four grades, it fails to sort well between grades for all properties.
2. The code of practice is impractical for use with in situ timber elements due to the use of RoG. However, this is a simple visual grading code to apply to new timber.
3. Knot clusters and single knots are the most important visual grading measures, perhaps due to the slightly relaxed limits for RoG.

4.4.3 CP112

A conference paper presented at the Shatis’19 conference provides details of this assessment of CP112 (Bather and Ridley-Ellis, 2019). What follows is just one figure from the conference presentation which serves to illustrate the key outcomes in relation to the grading and testing to destruction of the 143 Norway spruce test pieces.

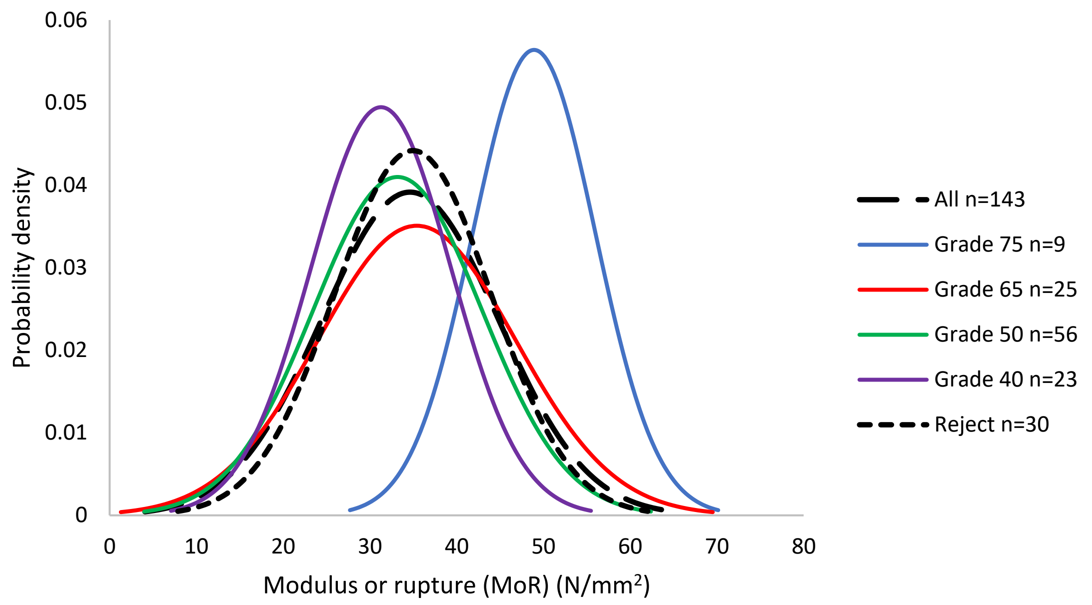

Figure 4.5. Probability density function for Norway spruce, showing the four different visual grading categories of CP112 (plus Reject)

Figure 4.5 shows the probability density functions of the test pieces, broken down into the four grades of CP112 plus Reject. It is seen that the mean bending strength of the 30 'rejected' joists is slightly higher than that of two of the four grading categories and broadly the same as for a third category and for all joists together. Thus, CP112 appears to be able to differentiate the higher grade only.

The rationale for CP112 is the same as for the other current national visual grading codes of practice and so its lack of precision comes as no surprise. Figure 4.5 illustrates the inability of the visual grading method to separate out timber joists clearly and consistently into tightly defined groups of similar properties. However, as for all of the grading codes, CP112 has some success in separating out the strongest group of joists into the highest grading category.

4.4.4 Discussion of the determination of characteristic values

The calculation of the characteristic values of the sample of minor species is carried out in accordance with EN14358 (CEN, 2016a) and the code itself should be referred to for a fuller understanding. The code leaves room for judgement to be exercised, for instance, (i) where a sample is borderline normally distributed or logarithmically normally distributed or (ii) whether to use the parametric or non-parametric approach or (iii) whether to use the simplified expression for $k_s(n)$ or the tables in the code (additionally, an approach based on statistical first principles could be adopted).

Further judgement needs to be exercised on the treatment of samples. For instance, in this study, the samples could be treated in a number of ways: all data together in a single sample of 'minor species', splitting the samples by species, by growth areas or by both species and growth areas.

Different characteristic values are calculated depending on the choice of approaches. So, the characteristic values using three approaches are compared. Despite being borderline normally distributed, a lognormal distribution of MoR data is assumed. Normal distributions of MoE and density and a lognormal distribution of MoR were found to be reasonable and thus did not require the use of a non-parametric approach.

With regard to the final adjustment of characteristic values in accordance with EN384, three approaches are considered. Approach 1 considers all species together as a single visually graded sample. Approach 2 considers each of the four species as a sub-sample of a larger sample (n=527). Approach 3 considers each species in turn as a single sample. Adopting these three different approaches for MoR, density and MoE and using the Formulae 11, 12 and 13 of EN384 leads to different characteristic values.

For each of the three approaches, the characteristic values of the joists are determined for the relevant properties, in each of the visual grading categories (and hence, the associated strength classes of EN338). Approach 2 typically delivers the highest characteristic values but requires each species to be treated as a sub-sample of a larger sample. This inevitably leads to smaller sample sizes which significantly affect calculated values. This effect occurs to an even greater degree with Approach 3.

In this study, the key purpose of visually grading and then allotting to strength classes is to assess the ability of the visual grading codes to differentiate between say weaker and stronger joists. It is not to determine the absolute calculated characteristic values for each grading category. If one approach generally leads to slightly elevated calculated characteristic values relative to the other approaches, it is unimportant, as long as it is possible to assess the differences between the calculated characteristic values. In this study, it is considered most appropriate to use Approach 1, which treats all four species as if they are from a single population and subsequently allows sample sizes for grading categories to be larger (and so better) than for Approach 2. This approach also accords best with the approaches to build predictive models which are not dependent on species.

As noted above, the calculated characteristic values of MoE and MoR rise with each increasing visual grading category for all three visual grading codes but for density, this only occurs with BS4978. Characteristic densities fluctuate with no pattern between visual grades for DIN4074 and INSTA142.

4.5 Discussion

4.5.1 Gap in the literature on visual grading

The literature review found research considering the efficacy of visual grading codes focussing on: (i) yields and (ii) characteristic values. Quite reasonably, almost no research considers the issue of key importance in the appraisal of individual in situ structural timber elements; namely, the accurate sorting of individual elements into narrowly defined groups with similar properties.

4.5.2 Similarities of and differences between visual grading codes

The Eurocodes have successfully created a harmonised inter-continental process for strength grading (including the creation of samples, laboratory testing, visual grading, strength classification and marking, etc.) and structural design. This encompasses and relies on the use of several national visual grading codes of practice which have been developed in diverse ways to accord with local conditions, leading to a series of divergent documents which in outline, agree with each other but in detail, differ significantly.

4.5.3 Visual grading is broad brush and imprecise

Even when carried out for timber from a designated growth area and for a single species, visually graded groups of timber have widely ranging mechanical and physical properties. This is due to a number of reasons including:

(i) visual grading features are only weakly correlated with mechanical and physical properties
(ii) each of the grade determining properties does not vary perfectly in step with the others and so stiff joists may have low bending strength, etc.
(iii) the relatively closely grouped categories of a visual grading code (compared with the overall variation of properties of timber) will necessarily contain joists with a wide range of properties

Visual grading followed by strength classification is therefore a broad brush method, which, even if it were to work perfectly, would lead to conservative outcomes (so much so, that it would be of limited use to a structural engineer appraising in situ structural timber in a borderline situation). Additionally, its ongoing use for new timber should be questioned due its relatively wasteful and conservative outcomes. Please refer to Chapter 9 for a discussion on this point in relation to climate change.

The inability of the visual grading codes to sort joists into groups with different mechanical and physical properties is illustrated by the graph presented for CP112 and by the outcomes of the t Tests which found that several visual grading categories are not significantly different to other categories.

Nevertheless, the visual grading codes did manage to indistinctly sort timber into groups whose physical and mechanical and physical properties had a general tendency to increase in line with visual grading categories. This shows some success for visual grading and suggests that the visual grading features have some predictive power.

4.5.4 Growth areas important but difficult to know for in situ timber

The current system of structural grading requires visual grading codes and their grading categories to be tied to specific growth areas and species (typically limited to the commercially important ones). This prevents the visual grading of outlying minor species/growth areas and so in this study, estimates were made to link the three visual grading codes with the four minor species grown in the UK. The analysis of the results of the grading show that these estimates do not work (i.e. did not sort timber into groups whose characteristic values reliably accorded with Table 1 of EN338) and need adjusting.

The inappropriateness of the estimated links serves to illustrate one of the dangers of applying visual grading codes to in situ structural timber of unknown growth area or species. From the literature review, it is known that growth areas significantly affect the mechanical and physical properties of timber and in practice, even though it is possible to determine the species of in situ structural timber element, it is unlikely that its growth area can be known. Thus, a predictive model that accounts for this variance but functions without the need to know growth areas (or species) would be useful.

4.5.5 Visual grading features

It is worthwhile considering the visual features used in the three visual grading codes. Firstly, the test pieces in this study, cut from relatively young trees, grown in the UK have wide growth rings which combine badly with the limits placed on RoG by the three visual grading codes. So, with the tight limits placed on RoG by DIN4074, almost half of the test pieces have their grade determined solely by RoG, and with the more relaxed limits of INSTA142 only around one tenth are rejected in this way.

Two of the three visual grading codes place over one third of the test pieces in the Reject category, thereby, giving no useful indication of these joists' mechanical and physical properties, other than that they have values lower than the weakest grades. This is a significant handicap exacerbated by the fact that many of the Reject grading is due to RoG which is typically impractical to measure in situ.

Secondly, due to the presence of so many factors in the visual grading codes reviewed, no clear conclusions can be drawn between the use of single knots, knot groups and knot clusters. So, this is considered further in Chapter 5.

Thirdly, it may be that the sample of minor species in this study is of unusually straight grained timber, but SoG was found to be the sole grade determining factor only a handful of times, regardless of the visual grading code used. This, together with its weak correlation with the physical and mechanical properties of timber lead towards to the conclusion that it is unlikely to form a particularly useful part of a predictive model.

4.6 Conclusions

The three visual grading codes used in this chapter are poor predictors of the mechanical and physical properties of individual timber joists. This outcome was expected and reflects the inappropriate use of the codes in this context rather than a fault in their use as intended (grading large numbers of timber elements from known sources for commercial purposes).

The three visual grading codes accomplish the same job, with similarly poor results, using a variety of ways of defining visual features, measuring them and comparing them to the dimensions of the original timber joist in order to grade them. The differing visual grading parameters are investigated further in Chapter 5 to determine the most useful of them in relation to in situ timber assessment.

Strength classes are based on the worst performing parameter of the three key mechanical and physical properties of timber. As such, they may reflect well, one of these properties, and give very little indication of the other two properties. For instance, a joist classed as Reject due to its low MoR may have an MoE suitable for classification as C24. There were many joists with low MoR values in the sample used in this study and even though they may not be representative of the majority of the timber elements found in situ in the UK, this does not undermine the conclusions made in this chapter.

Chapter 5 Visual grading parameters

5.1 Introduction to the chapter

The purpose of this chapter is to describe and discuss the visual grading parameters that could potentially be useful in creating predictive models for the mechanical and physical properties of in situ structural timber elements. Of particular interest are the several ways in which knots can be measured in relation to the joists in which they reside to create a variety of knot ratios.

It is proposed that the predictive model is flexible to relate to conditions found on site during many in situ assessments. So, for instance, all four sides of a joist may be visible and available for inspection or perhaps only three sides may be visible, or just two, etc. A model that can account for varying input like this will be more useful to a practising engineer than a model that is built on the basis of a full set of input data, as per the data available in this study. Thus, the number of knot ratios is extended to include different numbers of faces on which knots are measured and then combined.

A literature review is carried out on the visual features (and their measures) that are typically used in visual grading codes of practice. Next, two approaches which assume that knots act as voids are considered and analysed to allow their appraisal later in the chapter.

Then, using the results from the testing of the four minor species, the best way to measure the various visual features is provisionally determined, through consideration of correlation with measured properties. Finally, the results are discussed and conclusions drawn in relation to the predictive models under construction.

Unique contributions to knowledge described in this chapter are:

(i) The development of new flexible knot ratio measures with stronger correlations with the mechanical properties of timber joists than the measures used in current visual grading codes of practice
(ii) The demonstration of the weakness of the relationships between the mechanical properties of timber joists and section moduli calculated by treating knots as voids.

5.2 Review of visual grading parameters

Visual grading when linked with strength classification primarily makes use of visual features but also includes species as a factor. In this sub-section, the features used in the visual grading codes are reviewed.

5.2.1 All features used in the visual grading codes

There is general agreement about the overall approach to visual grading between the three national grading codes, and there are many differences in detail (as also noted in Chapter 4). These are apparent in the different limiting dimensions or ratios for individual visual features in the different visual grading codes. Broadly, knots, SoG and RoG have detailed, stepped limits for each visual grading category and so these features chiefly determine the grades of joists.

The SoG and RoG factors are determined in the same way in each code. But although knots are initially measured in similar ways in each code, these measurements are then converted to different knot ratios. BS4978 considers knot clusters up to a length of 150mm and converts knot dimensions into knot area ratios (KARs) and differentiates between overall KARs and margin KARs which occur close to the top and bottom edges of joists. INSTA142 considers knot clusters up to a length of 100mm (for the test pieces in this study) and uses knot dimension ratios, with differing limits for knots present on wide vertical faces and knots on narrow horizontal edges. A distinction is also drawn, between the knots close to the mid-height of a joist and margin knots near to the top and bottom edges. For the sizes of joists in this study, DIN4074 only considers single knots and uses knot dimension ratios but does not differentiate between wide vertical face knots and narrow horizontal edge knots; nor does it use the concept of margin zones. None of these three visual grading codes makes use of knot groups.

Additionally, the approach taken to measuring knots in visual grading codes can be either absolute or ratio. CP112 specifies knot dimension limits for specific cross sectional sizes and INSTA142 and DIN4074 specify knot dimension ratios.

Other visual features which are included in the visual grading codes are typically included to control the overall quality of the timber joists being graded, rather than to help sort into different visual grades. These are shown in the grey shaded cells in Table 5.1, which summarises the above.

Table 5.1. Visual features used in visual grading codes (DIN4074, INSTA142 and BS4978)

Visual feature	DIN4074	INSTA142	BS4978
Single knot *	Yes	Yes	Yes
Knot group	No	No	No
Knot cluster	No	Yes	Yes
Differentiate between narrow edge and wide face knots	No	Yes	No
Differentiate between knots in mid-height and top and bottom margin zones	No	Yes	Yes
SoG *	Yes	Yes	Yes
RoG *	Yes	Yes	Yes
Pith	Yes	No	No
Through thickness cracks *	Yes	Yes	Yes
Not through thickness cracks *	Yes	Yes	Yes
Wane *	Yes	Yes	Yes
Distortion *	Yes	Yes	Yes
Discoloration	Yes	No	No
Fungal damage *	Yes	Yes	Yes
Compression wood *	Yes	Yes	Yes
Insect damage *	Yes	Yes	Yes
Resin pockets (*)	No	No	Yes
Bark (*)	No	Yes	Yes

* Directly required by EN14081 (*) Indirectly required by EN14081

The limited literature review found no direct comparisons between the correlation of the various methods of defining knot ratios with strength properties, although a number of studies conclude that KARs are better correlated to strength properties than simple knot dimension ratios (Thelandersson and Larsen, 2003).

Visual grading parameters are weak predictors of mechanical and physical properties as illustrated in Table 5.2, which shows correlation coefficients with regard to bending strength of European spruce. The correlation coefficient for knots has been increased by using KARs in place of simple dimension knot ratios, especially by separating mid-height knots and margin knots (Thelandersson and Larsen, 2003).

Table 5.2. Correlation coefficients, r, between possible grading characteristics and strength properties for European spruce (Glos, 1983)

Grading parameter	MoR (bending strength)
Knots	0.5
Slope of grain	0.2
Density	0.5
Ring width	0.4
Knots and ring width	0.5
Knots and density	0.7 – 0.8
MoE	0.7 – 0.8
MoE and density	0.7 – 0.8
MoE and knots	> 0.8

It should be noted that visual grading codes assess knots, slope of grain and density as individual factors which are not combined. Instead, all of the factors are assessed individually and the worst case is adopted. The correlation coefficients presented in Table 5.2 indicate very weak or weak coefficients of determination for single predictors which can be improved by combining to become moderate. For instance, knots and density improve from individual r values of 0.5 to a combined r value of between 0.7 and 0.8.

In this chapter and the following chapters, descriptive terms are used for the strengths of relationships based on coefficients of determination or correlation coefficients and these are defined in Table 5.3.

Table 5.3. Descriptive terms used for the strengths of relationships

Coefficient of determination (r^2)	Correlation coefficient (r) (rounded values)
0 indicates no relationship	
Very weak	
0.2	0.45
Weak	
0.4	0.65
Moderate	
0.7	0.85
Strong	
0.9	0.95
Very strong	
1 indicates a perfect relationship	

5.2.1.1 Introduction to knots

Despite there being many different types of knots (e.g. checked knot, tight black knot, intergrown knot, not firmly fixed knot, spike knot, sloughed knot and unsound knot (Softwood Export Council, 2004)), visual grading codes do not typically differentiate between them. Part of the reason for this is that one understanding of the importance of knots is in relation to the grain deviations around knots, rather than the type of knot (or the knot itself); it is the grain deviation that most strongly correlates with reduction in strength (Glos, 1995). One understanding of the effect of knots is that the knot stands as a proxy for this grain deviation (and perhaps also for radial position and other indirect factors such as forestry practices), and so, for example, in the UK, the visual grader does not have to directly allow for grain deviation around knots as the '*appropriate allowance has been calculated and checked by extensive testing in research establishments'* (Tredwell, 1973, page 11). An equally common but alternative understanding of the effect of knots on strength is to model the knot as a void which naturally reduces the cross sectional area of wood resisting any applied forces. This is discussed in more detail in Sub-section 5.3.

As the size and type of stresses over a cross section of a piece of timber in bending vary with distance from the neutral axis, so some codes of practice penalise knots differently according to their distance from the neutral axis. There is a general belief that knots located in a region where high tensile stresses will occur in bending will more significantly reduce bending strength than knots located elsewhere (Piazza and Riggio, 2008; Yeomans, 2019b).

So, in the three visual grading codes used, different minimum values of knots (for inclusion in the grading process) are adopted; knots are defined and measured differently (minimum diameter, minimum height or width) and knots are compared to their joist face and edge dimensions in different ways, creating different ratios. Finally, the extent of knot groups and clusters are limited in different ways.

5.2.1.2 Knot groups, knot clusters and single knots

The terms knot groups, knot clusters and single knots require defining and the length over which these are measured needs consideration.

Measurements are described in different ways in different codes of practice (EN844-9, INSTA142, DIN4074, CP112 and BS4978) with little agreement over the way that knot clusters are determined and no guidance on the use of knot groups (CEN, 1997b, Dansk Standard, 2009, German Institute for Standardisation, 2012, BSI, 1971, BSI, 2017).

BS4978 is based on the projected areas of knots (compared to the cross sectional area of the joist) and the consideration of knot clusters (which are the basis of the knot area ratios) is integral to its methodology. It is written to be used by professional timber graders and as such has a complexity beyond the other visual grading codes of practice. Even professional timber graders have difficulty applying KAR rules consistently (Courchene, Lam and Barrett, 1996). Due to this, and its difficulties of use on site, the method of using KARs is not an appropriate knot measure for in situ timber.

As almost no agreement is found between the codes, for the purposes of determining useful visual grading parameters, consideration is given to three variants of knot measurement (with definitions used in this study):

i. single knots are measured, ignoring the presence of all other knots
ii. knot clusters comprise all knots within a specified length along the span of a joist, regardless of their perceived effect on each other and overlapping of knot dimensions is accounted for
iii. knot groups comprise all knots within a specified length along the span of a joist, regardless of their perceived effect on each other and overlapping of knot dimensions is ignored; so, the total sum of knot diameters is calculated.

All three variants are considered as well as a range of lengths (from 50mm to 500mm) to assess the most useful.

5.2.1.3 Knot measures

Knot measures broadly fall into two types: knot area ratios (KARs) and knot dimension ratios. Knot area ratios have slightly better correlations with strength properties than dimension ratios and both knot measures can be refined to account for the location of knots within a cross section of a joist and this again improves correlations. For instance margin KARs used together with total KARs improve correlations. This is a slight improvement to a weak or very weak correlation.

A comparison of the British and German methods for measuring KARs shows how two knot measures characterise a sample of joists quite differently. The two measures themselves correlate weakly or very weakly with each other and lead to the contradictory situation of some knot configurations having low KAR measures and high DEK measures and vice versa (Stapel, van de Kuilen and Strehl, 2012).

More generally, a literature search did not lead to any useful information on the most effective form of knot measure. In any case, almost all grading related research is limited to the key commercial species and so its efficacy on other species would be unknown. Instead, the results from the testing of the minor species sample of timber used in this study can be used to draw some tentative conclusions (refer to Table 5.5 and associated discussions).

5.2.1.4 Rate of growth

Rate of growth is ‘known’ to correlate reasonably well with both MoR and MoE (Forest Products Laboratory, 2010; Coulson, 2012; Morales-Conde, Rodriguez-Linan and Saporiti-Machado, 2014). However, that rate of growth has a poor correlation with density for some species, has been found in other studies (Grant, Anton and Lind, 1984; Fernandez-Golfin Seco and Diez-Barra, 1996). An explanation for the poor correlation is presented by Davies (2016) based on how the inner diameter of conducting cells change from earlywood to latewood. As this varies significantly by species (Forest Products Laboratory, 2010), although RoG may be a useful indicator for density in some species, it is not for all species and this is a reason to not use RoG in a species-free predictive model for density. It is worth noting that RoG is required by EN14081 as, of all visual features, it has the strongest correlation with density but it may be omitted if a direct density measure is obtained.

RoG is measured and described slightly differently in national visual grading codes of practice. However, it is always a measure of the number of growth rings within a given length. The measurement of RoG of a loose joist that can be picked up and turned in one’s hands is relatively easy. However, it is not practically possible to do this for an in situ joist in an existing structure. Typically, joist ends are built into walls or may butt up to other joists and so are not easily accessible. The advice in the EN17121 code of practice is that rate of growth '…*can be estimated through coring and/or micro-resistance drilling in perfectly radial direction*' (CEN, 2019b, p. 18) is not considered practical as the surface appearance of wood grain and growth rings on the longitudinal faces of a joist are not enough to reliably predict the cross sectional pattern of growth rings.

So, despite the potentially useful weak predictive power of RoG for some individual species, as is discussed above and in Chapter 1, it is impractical to gain access to one or both ends of a timber joist, to measure RoG in situ and so it is considered impractical to include RoG in a species free predictive model.

5.2.1.5 Slope of grain

In visual grading of timber, the slope of grain is a measure of the '*divergence of the direction of the fibres from the longitudinal axis of the piece'* (CEN, 1997b, p. 8). This property can, on occasion be assessed by measuring fissures and splits that occur between the fibres of wood. However, in the absence of these, slope of grain can only be assessed with certainty by the use of a swivel handled scribe. Grooves must be scored into the surface of the timber joist. From measurement of these groove lines, the overall inclination of the grain to the longitudinal axis of the timber joist can be determined on each face.

Slope of grain can be a two dimensional (2D) measure, based on just one face, usually the wide face of the element. SoG may also be a three dimensional (3D) measure, combining the measures from two perpendicular faces (wide and narrow faces) to give the overall deviation from the longitudinal axis. Its value is typically presented as a unitary deviation (e.g. 1 in 10 or 1 in 12) in some codes (Dansk Standard, 2009; BSI, 2017) which is a non-linear scale. However, a presentation as a decimal or as a percentage is used in other codes and provides a scale easier to accommodate in statistical analyses (Deutschen Institut für Normung, 2012).

Visual grading codes make use of the 'overall' measure of SoG and not the 'worst case' measure (Deutschen Institut für Normung, 2012; BSI, 2017). This differs from the way that the worst case measure of knots is used to determine a visual grade and it is inferred that the SoG measure is used as a predictor for the overall property of bending stiffness rather than the local property of bending strength. If, as is asserted, SoG has a significant effect on MoR, then ignoring steeply angled slope of grain present in a joist can only be explained by its difficulty of being defined and measured.

Visual grading codes make use of the overall 3D deviation of the grain (as opposed to the worst case deviation of the grain, say, around knots) and two 2D measures (e.g. 1/18 and 1/12) taken on adjacent faces of a joist are combined to give the 3D measure, for example:

$$\sqrt{\left(\frac{1}{18}\right)^2 + \left(\frac{1}{12}\right)^2} = \frac{1}{10} \qquad i.e. a\ slope\ of\ 1\ in\ 10, or\ 10\%\ or\ 0.1 \tag{5.1}$$

The 3D measure is preferred as it more thoroughly captures the slope of grain in a timber element. For instance, severe SoG on a narrow face could be ‘missed’ by taking only one 2D SoG measurement on the wide face.

The comments in this sub-section apply to softwood. Additionally, SoG is an important visual feature of hardwood, which typically having fewer and larger branches cannot rely on knot measurements for visual grading to the same degree.

The justification of the use of SoG is based on large scale testing of small clear specimens in the USA (Silvester, 1967) which combines well with a theoretical mechanical analysis of the behaviour of the anisotropic material of wood. As the tensile strength of timber perpendicular to the grain may be as little as 2.5% of the tensile strength of timber parallel to the grain, the strength of a timber joist is greatly reduced if its grain is oriented to transmit longitudinal tensile forces perpendicular to the grain (Forest Products Laboratory, 2010).

Due to the complex fibre composite structure of wood, the manner in which SoG affects bending strength is not straightforward, for instance, tensile forces are transmitted longitudinally along the grain of wood, from one long thin overlapping tracheid cell to the next. The forces within each tracheid are transmitted primarily in tension through the cellulose molecules in the S2 layer of the cell wall, which are strong in tension. Whereas the forces between overlapping tracheids are transferred in shear.

For sawn wood with high SoG, tracheids are exposed at the cut edges of a joist which breaks the continuity of the overlapping tracheids and realigns the tensile and shear forces between tracheids. As SoG increases, more tracheids are exposed at the sawn lower edge of a joist and greater tensile forces develop between tracheids.

Cross-grain or cross-tracheid tensile failure takes place between tracheids (Smith, Landis and Gong, 2003) and this is known to vary significantly between-regions, between-trees, and within-trees, even for a single species from a limited growth area (Grekin and Surini, 2008). However, shear failure occurs through the cell walls of the tracheids as opposed to the failure of the connection between overlapping tracheids (Luostarinen and Heräjärvi, 2018). So, it is seen that the behaviour of the wood itself is not straightforward and is subject to the many differences between wood from differing forestry practices and from different species and growth areas.

Many studies show poor correlations between slope of grain and bending strength (Zhou and Smith, 1991; Glos, 1995b) and so, for a species-free predictive model for timber from many eras and growth areas, it is unlikely that SoG will be a particularly useful predictor variable.

5.2.1.6 Wane and relationship to pith

INSTA142 and BS4978 both limit wane to a total of 33% of any given face of a timber element for all grades. DIN4074 limits wane to 25% for its two lower grades and to 20% for its higher grade. CP112 limits wane to 10% for its two higher grades and to 20% for its two lower grades.

Firstly, for the sale of new timber, limitations on wane serve a few purposes:

- They ensure the squareness and appearance of timber elements
- They provide a minimum face for nailed connections and bearings
- They ensure a minimum cross sectional area of a structural timber element

For the structural appraisal of in situ structural timber, there is nothing to be gained by rejecting a timber element based on a general limit for wane when instead, an engineer or carpenter or architect can consider the specific dimensions of the timber element in place and use their judgement.

Secondly, as visual grading codes are typically based on local practices and include rules that have been shown to work satisfactorily over time, it is considered that there may be reasons for the need to limit wane, other than those above. It may be that wane is related to the mechanical and physical properties of the wood, or is indicative of tree diameter, log position or straightness.

It has been shown that there is a general trend for Sitka spruce and most commercially grown conifers, of improving mechanical and physical properties of wood, running from pith to bark (Moore, Lyon and Lehneke, 2012). As wane can only be present adjacent to the bark, this suggests that, at least for Sitka spruce, wane is a good indication of better properties than, for instance pith. This is worthwhile investigating further, however, for this study, wane is not used in any of the predictive models.

5.2.2 Other factors

5.2.2.1 Density

Density is itself is an indication of the amount of wood substance contained in a timber element, and as more of this would be expected to lead to more strength and greater stiffness, density is also thought of as a useful predictor of these mechanical and physical properties of timber (Piazza and Riggio, 2008). For many softwoods, density is inversely related to annual ring width, leading to RoG typically being included in visual grading criteria. Despite the logical argument for density being a strong predictor of bending strength, it is only weakly related to MoR and as RoG is only weakly related to density, RoG is an even weaker predictor of MoR.

5.2.2.2 Species

Species is currently used as a key grading indicator in the Eurocodes, despite some criticism, as (i) it provides limited information regarding the mechanical and physical properties of timber, (ii) few structural engineers can tell one species from another and (iii) the assessment of mechanical and physical properties using NDT and SDT combined with visual inspection can be made successfully without knowledge of species (Nwokoye, 1975). Additionally, for practical reasons and as discussed in Chapter 1, predictive models without species are preferred to ones including it. Hence, this study focusses on the commonly found softwood species in the UK building stock and no further consideration will be given to this factor.

5.2.2.3 Size limits and size effects

Both INSTA142 and DIN4074 restrict the use of their tables of limits of grading features to timber joists of certain sizes. BS4978 limits its application to timber joists with a minimum width of 20mm and with a minimum cross sectional area of 2000 mm^2. None of the codes have an upper limit on their applicability. The adjustment of visual grading limits according to size is likely to relate to local forestry, saw milling and construction practices and size effects.

In engineering materials, the probability of failure under stress of a larger volume of material is greater than for a smaller volume. Therefore, it would be expected that timber elements with larger cross sections would be weaker than those with smaller ones (Weibull, 1939), even if the wood that they comprised was identical. The use of this theory applies well to tension and shear in timber but has been found to have mixed results when applied to bending and compression. One possible reason for this is that knot sizes in large trees are bigger than in small trees and so knot sizes tend to increase along with the size of timber (Rouger, 1995), additionally, older trees tend to have fewer knots and less juvenile wood.

Over several decades, the testing of structurally sized test pieces has shown that typically, bending strength varies with member size and method of loading. In this particular class of research, the results of studies can be found to be contradictory. So, although many studies show the existence of size effects, others do not. Factors such as size of trees and logs, log quality and cutting pattern (orientation and radial position) influence results.

For visually graded timber, size effect parameters may be anisotropic, for example, changes in member width causing greater size effects than changes in member length. Additionally, size effects, have been found to be greater for weaker wood than for stronger wood (Barrett, Lam and Lau, 1992); and conversely, greater for stronger wood than for weaker wood (Madsen and Nielson, 1978). Nevertheless, the effect of size on strength of timber is generally accepted and is dealt with in the Eurocodes in two parts: firstly, in the grading process and secondly, in the design process.

As noted in Sub-section 3.2.2.1, in the grading process of commonly used softwoods, 5 percentile values of bending strength are adjusted (CEN, 2010) to a standard 150mm depth by dividing by factor k_h :

$$k_h = \left(\frac{150}{h}\right)^{0.2}$$

In the design process, timber beams with depth less than 150mm have their strength adjusted (CEN, 2006) by the factor k_h :

$$k_h = min\begin{cases}\left(\frac{150}{h}\right)^{0.2} \\ 1.3\end{cases} \tag{5.2}$$

As an illustration of the disparities between the several approaches to size effects, the Eurocode approach is compared to a large scale study made by Fewell and Curry, who analysed size effects, combining around 4000 test pieces at Princes Risborough Laboratories together with a further 4000 or so test pieces from Canada (Fewell and Curry, 1983). Firstly, they found no statistically significant interaction between grade and section depth; secondly, they concluded that the size effects in their data are best described by the following equation, relating to a standard depth of 200mm:

$$K = \left(\frac{200}{h}\right)^{0.4} \tag{5.3}$$

Thirdly, they concluded (in a similar fashion to the Eurocodes) that the equation can be applied without the need to distinguish between species or visual grades. The equation derived by Fewell and Curry (referring to a 200mm datum) does not accord well with the equation for size effects in the Eurocodes (referring to a 150mm datum), even when adjustments are made to the datums used by each. Reference should be made to Figure 5.1 below.

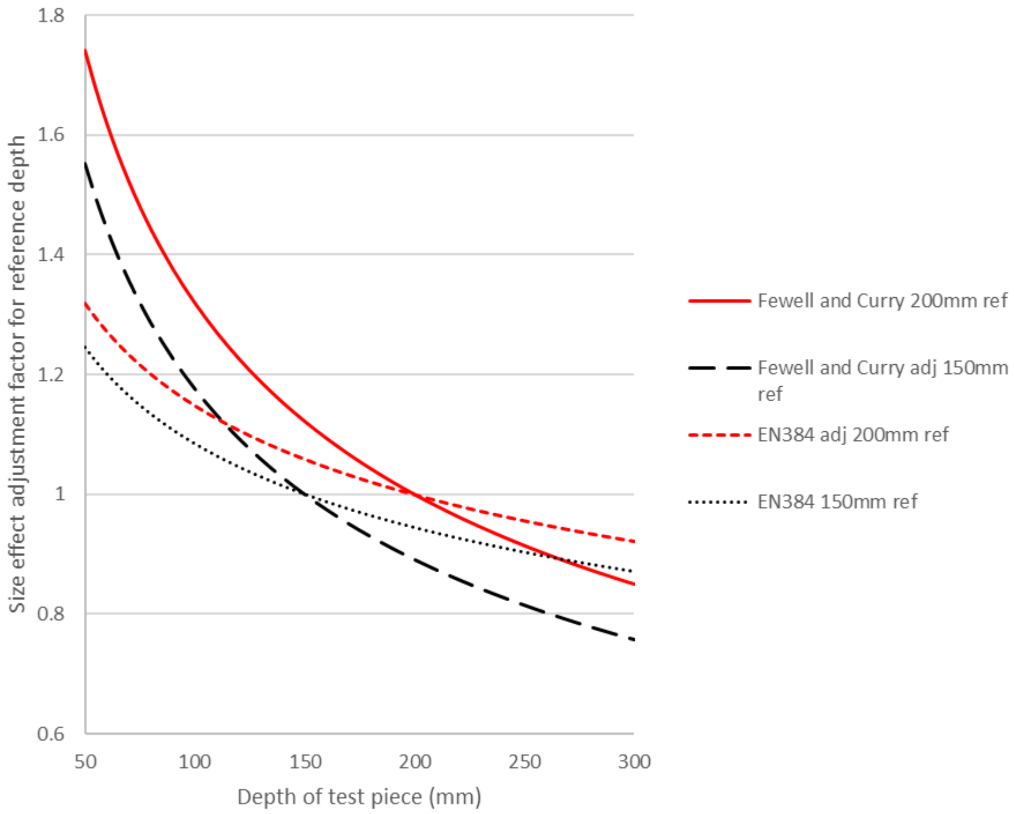

Figure 5.1. Comparison of size effect factors

In this study, the nominal depth of test pieces is 100mm and size effect adjustment factors given by the two equations (for several depths of test pieces) are given in Table 5.4 below.

Table 5.4. Size effect factors based on 150mm and 200mm datums

Depth of test piece (mm)	Adjustment factor based on 150mm datum		Adjustment factor based on 200mm datum	
	EN384	Fewell and Curry (adjusted)	EN384 (adjusted)	Fewell and Curry
100	1.08	1.18	1.15	1.32
150	1	1	1.06	1.12
200	0.94	0.86	1	1

It is seen that although there is agreement that size effects are present, the strength of these effects, based on 100mm test pieces, ranges from an 8% to 18% increase (results based on the 150mm datum) and from 15% to 32% increase (results based on the 200mm datum). It is beyond the scope of this study to investigate this phenomenon further, however, with such large variations between predictions, it is clear that this is a potentially significant source of error in any model derived. This is particularly the case as the size of modern test pieces used in a potential model may not relate well with the typical sizes of in situ timber elements. The approach proposed in the Eurocodes will be followed to allow a direct link between the outcomes of this study and the Eurocodes used by engineers in practice.

5.2.3 Analysis of two approaches which consider knots as voids

In structural engineering literature, the correlation between, knot ratios and MoR, has been interpreted intuitively as a causal relationship, with knots defined as '*strength reducing defects*' (McKenzie and Zhang, 2007, p. 7) and the key influence of their presence being ''*their effective reduction of the modulus of the section*' (Ozelton and Baird, 1976, p. 29).

The assumption of causal correlation between knots and MoR has led to some visual grading codes to treat knots sizes as being directly related to MoR. For instance, the American code of practice ASTM D245 treats face knots as voids and bases adjusted strength reduction factors (SRs) directly on reductions of elastic section moduli due to the presence of knots (acting as voids) (ASTM, 2019). Strength reduction factors (SRs) associated with knots in bending members can be derived as the ratio of moment-carrying capacity of a member with cross section reduced by its largest knot to the moment-carrying capacity of the member free of knots. This gives the anticipated reduction in bending strength due to the knot. For simplicity, D245 treats all knots on the wide face as being either knots along the edge of the piece '(edge knots') or knots along the centreline of the piece ('centerline knots').

This approach is at least partially adopted by structural engineers assessing in situ timber (Yeomans, 2019a) and can be compounded by further misunderstandings of the methodology of visual grading and strength classification (Yeomans, 2003). Nevertheless, it has a seemingly logical and straightforward basis and, as it may provide a useful predictive tool for in situ timber, it merits further investigation.

As is explained in Chapter 1, this thesis is an exploratory study and as such it is worthwhile briefly reporting on the unsuccessful approaches investigated as well as the successful ones. Firstly, a series of Excel spreadsheets were created to carry out the calculations for the elastic section modulus of each test piece based on reduced elastic section moduli due to the presence of single knots (and additionally knot clusters) acting as voids. Secondly, the equations and methods used in D245 were used to determine SRs for each joist also. Both approaches were successfully used to determine the worst case SRs for each of the test pieces in this study and these were then compared with measured MoR and MoE. For a more detailed consideration of this topic, reference should be made to the supplementary document: “Technical note on the determination of strength reduction factors using elastic analysis”.

5.3 Results and discussion

5.3.1.1 Performance of knot ratios from visual grading codes

In planning for the predictive model it is useful to compare the differing coefficients of determination between the differing knot measures and MoR and MoE. This comparison is presented in Table 5.5 and allows the better (i.e. less weak) measures to be seen. Knot cluster and knot group measures are later extended to allow additional methods and different lengths of measurement to be considered.

Table 5.5. Coefficients of determination for knot measurement (BS4978, DIN4074 and INSTA142) with MoR and MoE. Shaded cells show the less weak correlations (green for MoR and blue for MoE).

	MoR	MoE
BS4978 - total knot area ratio based on single knots	0.039	0.007
BS4978 - margin knot area ratio based on single knots	0.130	0.034
BS4978 - worst case of either of the knot area ratios based on single knots	0.118	0.027
BS4978 - total knot area ratio based on knot clusters	0.188	0.148
BS4978 - margin knot area ratio based on knot clusters	0.182	0.084
BS4978 - worst case of either of the knot area ratios based on knot clusters	0.183	0.085
DIN4074 - knot ratio based on single knots only	0.171	0.118
INSTA142 - knot ratio based on knot clusters	0.191	0.124
INSTA142 - face knot ratio based on single knots	0.022	0.028
INSTA142 - edge knot ratio based on single knots	0.113	0.064
INSTA142 - worst case of either of the face or edge single knot ratios	0.096	0.054
INSTA142 – worst case of single knot ratios and knot cluster ratios	0.182	0.116

It is seen from Table 5.5 that firstly, for this sample of joists, all methods of knot measurement have very weak correlations, never exceeding 0.191 with MoR and 0.148 with MoE. Secondly, for both MoR and MoE, the greatest correlations are for knot clusters. Thirdly, simply combining knot cluster measurements with single knot measurements (by taking the worst case for each joist) does not improve correlations but worsens them. Fourthly, although DIN4074 relies solely on single knot measurements, its correlation coefficients (0.171 for MoR and 0.118 for MoE) are only slightly lower than the coefficients measured from knot clusters. Bearing in mind the relatively small sample size used for these comparisons, it is important not to over-fit the data but general trends can be seen. In summary, knot clusters perform the best in the above comparisons and are included in only two of the three visual grading codes, and none of the codes make use of knot groups.

5.3.1.2 Knot groups, knot clusters and single knots

The principle of the knot cluster, given above, can be extended in two ways. Firstly, knot cluster measurements can be taken over shorter or longer lengths of each joist. Secondly, a simpler form of measurement, that of a knot group can be used. Table 5.6 presents the coefficients of determination for each method of measurement over joist lengths varying from 50mm to 500mm. The knot ratio adopted for this analysis is adapted from INSTA142 and for knot clusters, is termed knot cluster1 (kc1). Its description is found in Table 5.7. The same approach is used for both knot clusters and knot groups.

Table 5.6. Coefficients of determination, r^2, of knot clusters and knot groups measurements with MoR and MoE. Shaded cells show the less weak correlations (green for MoR and blue for MoE).

Length of knot cluster or knot group	Knot clusters (i.e. accounting for overlaps)		Knot groups (i.e. no accounting for overlaps)	
	MoR	MoE	MoR	MoE
50	0.173	0.052	0.162	0.092
100	0.189	0.063	0.171	0.113
150	0.182	0.061	0.165	0.111
200	0.196	0.075	0.182	0.133
250	0.203	0.084	0.189	0.134
300	0.214	0.090	0.193	0.142
350	0.214	0.091	0.194	0.145
400	0.213	0.093	0.198	0.150
450	0.213	0.093	0.198	0.149
500	0.212	0.094	0.196	0.148

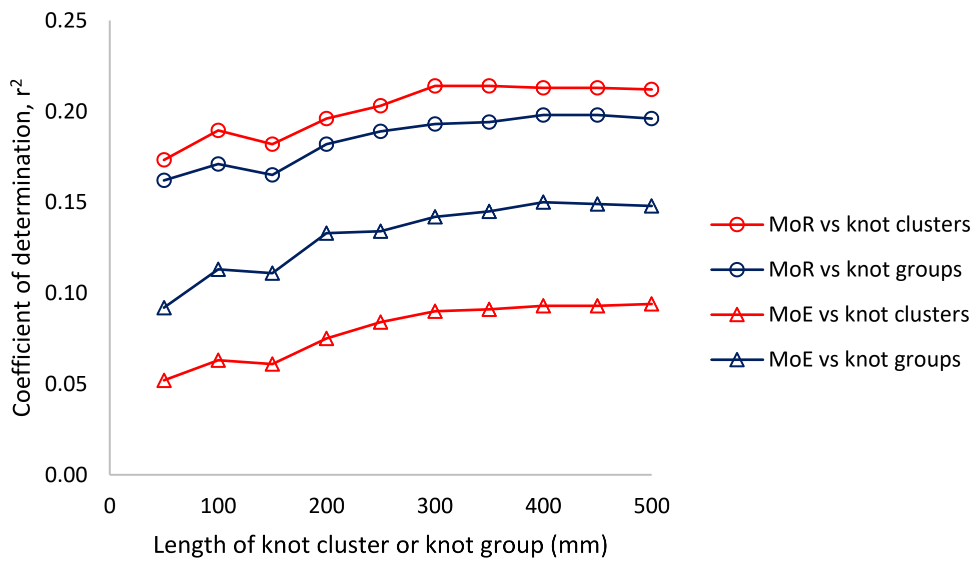

Figure 5.2. Comparison of coefficients of determination of knot clusters and knot groups with MoR and MoE

The coefficients of determination obtained are shown in Table 5.6 and Figure 5.2, where the measurement of knot clusters (compared with knot groups) gives higher coefficients of determination with MoR and lower coefficients with MoE. For MoR, for both clusters and groups, lengths of 300mm and greater give the highest coefficients.

For MoE, for both clusters and groups, lengths of 400mm and greater give the highest coefficients. It is worth noting that these lengths are much longer than the knot cluster lengths given in the codes of practice. Additionally, as knots were only measured within a 500mm long zone, many of the knot cluster and group lengths are effectively cut short due to lack of knot measurements. So, even though measuring knots is a slow and painstaking process, it could be useful to extend this work with studies of knots measured over longer lengths of joists. Bearing in mind the way in which each graph plateaus in Figure 5.2, it is not considered likely that significant improvements in predictive power will be found by extending lengths over which knots are measured.

Based on the above (and for the minor species data set) it is reasonable to adopt knot clusters (as opposed to knot groups) over a minimum length of 300mm when predicting MoR and knot groups (as opposed to knot clusters) over a minimum length of 400mm when predicting MoE.

The cumulative extent of knots within a length of a joist is a surprisingly fair indicator of MoE. It is already known that knots reduce the bending stiffness of a timber joist. For instance, Fink and Kohler (2014) showed that for Norway spruce joists, bending stiffness reduces by around 2 kN/mm^2 for total KARs of around 0.2 and that the reductions in bending stiffness are local to the knots. Rather than give an indication of the reduction in the cross sectional area of a joist (as measured by knot clusters) which is suitable for MoR, knot groups give a better measure of the overall volume of the joist affected by knots, which is more suitable for MoE.

5.3.1.3 Knot cluster measurements and ratios

The knot measurement method and knot ratio calculation used for Figure 5.2 use the knot measure formula in INSTA142 but extended over increasing lengths of assessment. This extension of area of assessment increases the strength of correlation between the knot ratio and MoE up to a point. On this basis, it is considered worthwhile to extend the knot measurement method to include all four faces of the joist (as opposed to just three faces of the joist as per INSTA142). Additionally, the formula used to calculate the knot ratio (based on the INSTA142 formula) is amended to create minor variations. Firstly, this is to try to derive a formula with better predictive properties and secondly, this is to derive a formula that may be more appropriate to common in situ inspection conditions whereby perhaps only three faces of a joist may be visible.

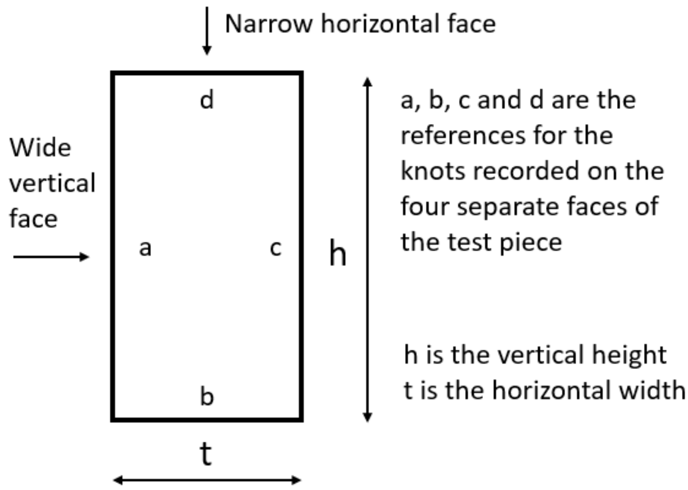

Figure 5.3. Labelled diagram of a cross section through a test piece

Table 5.7. Methods of calculating several knot cluster ratios, initially based on INSTA142 knot cluster ratio calculation

Reference	Formula	Comments
kc0	$\frac{max(a\ or\ c) + b + d}{h/_2 + t}$	This is an interpretation of the knot cluster ratio formula used in INSTA142. Only knots in the outer wide face are counted in the formula, and as this is not possible to determine from the research data, it is concluded that all knots on the outer wide face should be larger than the same knots on the inner wide face. Therefore, the maximum recorded measurement of knots from the two wide faces are used. In the denominator, the joist's vertical height h is halved. This reflects the doubly stringent visual grading restrictions for wide face knots (as opposed to narrow face knots) in Table 1 of INSTA142.
kc1	$\frac{max(a\ or\ c) + b + d}{h + t}$	Similar to kc0 but without the refinement of halving the joist height in the denominator.
kc2	$\frac{a + c}{2h} + \frac{b + d}{2t}$	This averages the knot group ratios for wide face and narrow face on an equal basis
kc3	$\frac{a + b + c + d}{2(h + t)}$	This is an overall average of all knots and all faces
kc4	$\frac{a + b + c}{2h + t}$	This only considers the two vertical wide faces and the bottom narrow face. This is likely to be a common condition on site when attempting to appraise in situ timber
kc5	$\frac{a + c}{2h} + \frac{b}{t}$	The first slight variant of kc4
kc6	$\frac{a + c}{h} + \frac{b}{t}$	The second slight variant of kc4 with greater weighting to the vertical wide faces
kc7	$\frac{a + c}{h} + \frac{b}{2t}$	The third slight variant of kc4 with even greater weighting to the vertical wide faces

Table 5.8. Coefficients of determination between various methods of calculating knot cluster ratios and MoR. Green shaded cells show the less weak correlations.

Length (mm)	kc0	kc1	kc2	kc3	kc4	kc5	kc6	kc7
100	0.189	0.189	0.162	0.209	0.201	0.167	0.197	0.201
200	0.196	0.197	0.178	0.222	0.207	0.173	0.200	0.207
300	0.214	0.214	0.177	0.230	0.214	0.187	0.211	0.213
400	0.213	0.213	0.179	0.230	0.217	0.189	0.213	0.217
500	0.212	0.213	0.179	0.229	0.215	0.189	0.212	0.214

For the general case of timber with all four faces accessible, it is seen in Table 5.8 that the highest correlation (r^2 = 0.230) is obtained with kc3, by taking all knot data from all four faces and simply dividing the knot cluster measurement by the perimeter of the cross section of the joist. The refinements of the knot cluster measures kc0, kc1 and kc2 serve only to reduce the coefficient of determination of the simpler averaging used in kc3.

For the particular case of timber with the top face inaccessible, the knot cluster ratios kc4 and kc7 have virtually the same correlations (0.214 and 0.213 respectively) for the knot cluster length of 300mm. As less information is available for the model in this case (three instead of four faces of knots measurements), it is logical that the correlation is weakened in comparison with kc3. The refinements of knot group measures kc5, and kc6 serve only to reduce the coefficients of determination in comparison with the simpler averaging used in kc4. Bearing in mind the small sample size and the possibility of over-fitting the data, it is considered that the simpler knot ratio measure of kc4 is preferred over the more refined kc7 knot ratio measure.

In an attempt to increase the predictive power of the data, a range of manipulations are investigated and the results are tabulated in Table 5.9 below. The coefficients of determination in the table are based on a knot group length of 300mm.

Table 5.9. Coefficients of determination between MoR and a variety of manipulations of knot cluster measures kc0 to kc7. Green shaded cells show the less weak correlations of interest.

	kc0	kc1	kc2	kc3	kc4	kc5	kc6	kc7
kc	0.214	0.214	0.177	0.230	0.214	0.187	0.211	0.213
1/kc	0.152	0.165	0.069	0.159	0.110	0.105	0.099	0.100
kc^2	0.167	0.167	0.129	0.179	0.161	0.145	0.162	0.160
1/kc^2	0.068	0.067	0.018	0.045	0.014	0.013	0.013	0.014
ln kc	0.228	0.229	0.176	0.244	0.224	0.203	0.220	0.222
1/ln kc	0.000	0.019	0.031	0.168	0.126	0.002	0.004	0.002
ln (1/kc)	0.228	0.229	0.176	0.244	0.224	0.203	0.220	0.222
ln (kc^2)	0.222	0.218	0.164	0.228	0.208	0.194	0.216	0.217

The knot cluster measures kc3 and kc7 are identified above as being promising as measures for predicting MoE. Their coefficients of determination without any manipulation (kc) are 0.230 and 0.213 respectively. By taking the natural log of the knot cluster measures (ln kc), the coefficient of determination is increased to 0.244 for kc3 and to 0.222 for kc7. This moderate increase suggests that it may be worthwhile to take the natural log of the knot ratio measurement. However, the natural log of the inverse of the knot cluster measures (ln (1/kc) is not considered further as its relationship with MoR is the same as the simpler unadjusted natural log. Finally, the inverse of the natural log (1/ln kc) reduces the strength of the relationship.

In summary, the knot cluster measures with the highest coefficient of determination with MoR are:

(i) assessed over a length of around 300mm or longer
(ii) simple averages of the sum of knot clusters divided by perimeter length of the joist cross section over which the knot measures are taken
(iii) possibly improved through additional manipulation (i.e. natural log)
(iv) best measured, where possible, over all four faces.

The knot cluster measures discussed above are extended further by considering scenarios that a structural engineer may encounter when assessing an in situ timber element. In an ideal world the engineer would be able to clearly see all four longitudinal faces of a joist. However, this may not be physically possible (for example for trimmer beams made up of two or three joists bolted together side by side) or a client may wish to limit the degree of disruption to an existing building (possibly still in use).

Thus, an engineer may not be able to measure the knot cluster measure kc3 and so a series of final predictive models could incorporate a range of different knot cluster measures that could realistically be all that an engineer could measure on site. Table 5.10 below illustrates how the range of knot cluster ratios in Table 5.9 could be extended. Further ratios could be used for instance for three faces (a, b, d and b, c, d) and for two faces (a, b and a, d and b, c and c, d and b, d) and for single vertical or horizontal faces (a and b and c and d).

Table 5.10. Knot cluster ratio measures suitable for some in situ scenarios

Reference	Formula	Comments
kc8	$\frac{a+c+d}{2h+t}$	This only considers the two vertical wide faces and the top narrow face. This could be considered to be the inverse of kc4.
kc9	$\frac{a+c}{2h}$	The sum of the two vertical faces divided by double the vertical height of the joist
kc10	$\frac{a}{h}$	The left vertical face of the joist divided by the vertical height of the joist
kc11	$\frac{c}{h}$	The right vertical face of the joist divided by the vertical height of the joist
Kc10 and kc11 combined	$\frac{a}{h}$ and $\frac{c}{h}$ combined	Although theoretically possible to differentiate between the inner and outer vertical faces of a joist, this is not possible when only one face of the joist is visible. Thus, for a single vertical face, any correlations must be based on the combined inner and outer vertical faces.

The correlation of each of these knot cluster ratios with MoR is presented in Table 5.11. This allows comparison of the scenario based knot cluster ratios and the ideal one of kc3 which contains information from all four sides of each test piece.

Table 5.11. Coefficients of determination between various methods of calculating knot cluster ratios and MoR, for some in situ scenarios. Green shaded cells show the less weak correlations.

Length (mm)	kc3	kc4	kc8	kc9	kc10/11
100	0.209	0.201	0.173	0.165	0.114
200	0.222	0.207	0.193	0.179	0.118
300	0.230	0.214	0.194	0.176	0.119
400	0.230	0.217	0.196	0.182	0.119
500	0.229	0.215	0.195	0.181	0.119

From Table 5.11, it is seen that the 300mm knot cluster measure could potentially be extended to 400mm or longer to provide more information on the fewer faces of the joists and so slightly increase the coefficient of determination. In a final predictive model based on a larger data set, the balance between gaining useful predictive information and the difficulties in collecting that information will need to be determined. For the purposes of this study, it is reasonable to continue with the 300mm length of knot cluster.

The scenario based knot cluster ratios are seen to have weaker coefficients of determination when compared with the ratio kc3 (based on all four sides of the test pieces). Interestingly, kc8 could be considered as the inverse of kc4 but including the top face in place of the bottom face. The ratio kc4 would be expected to have a stronger correlation with MoR as it includes knots measured including the bottom edge of the test pieces and it does. But neither of these ratios are as good as including knots in both top and bottom faces in the ratio (i.e. kc3).

The ratio kc10/11 is based on the correlation of each vertical face (considered separately) with MoR. Thus, (2 x 527 =) 1054 observations are included in the correlation calculation. The ratio kc9 is stronger than the ratio kc10/11 showing that the inclusion of both vertical faces of the test pieces improves upon just using one vertical face at a time.

Broadly, Table 5.9 and Table 5.11 show a general trend of stronger correlations with MoR associated with a greater number of observations (i.e. knot ratios including more faces of the test pieces) up to a point (i.e. up to lengths around 300mm or 400mm).

5.3.1.4 Knot group measurements and ratios

In a similar fashion to the variations of knot cluster measures trialled in relation to MoR, several very similar measures of knot groups were taken and then correlated with MoE. The variations in measurement are given in Table 5.12.

Table 5.12. Method of calculating several knot group ratios, initially based on INSTA142 knot cluster ratio calculation

Reference	Formula	Comments
kg0	$\dfrac{max(a\ or\ c) + b + d}{{}^{h}/_{2} + t}$	This is an interpretation of the knot cluster ratio formula used in INSTA142. Only knots in the outer wide face are counted in the formula, and as this is not possible to determine from the research data recorded, it is concluded that all knots on the outer wide face should be larger than the same knots on the inner wide face. Therefore, the maximum recorded measurement of knots from the two wide faces are used. In the denominator, the joist's vertical height h is halved. This reflects the doubly stringent visual grading restrictions for wide face knots (as opposed to narrow face knots) in Table 1 of INSTA142.
kg1	$\dfrac{max(a\ or\ c) + b + d}{h + t}$	Similar to kg0 but without the refinement of halving the joist height in the denominator.
kg2	$\dfrac{a + c}{2h} + \dfrac{b + d}{2t}$	This averages the knot group ratios for wide face and narrow face on an equal basis
kg3	$\dfrac{a + b + c + d}{2(h + t)}$	This is an overall average of all knots and all faces
kg4	$\dfrac{a + b + c}{2h + t}$	This only considers the two vertical wide faces and the bottom narrow face. This is likely to be a common condition on site when attempting to appraise in situ timber
kg5	$\dfrac{a + c}{2h} + \dfrac{b}{t}$	The first slight variant of kg4
kg6	$\dfrac{a + c}{h} + \dfrac{b}{t}$	The second slight variant of kg4 with greater weighting to the vertical wide faces
kg7	$\dfrac{a + c}{h} + \dfrac{b}{2t}$	The third slight variant of kg4 with even greater weighting to the vertical wide faces
kg8	$\dfrac{1000 \times (a + b + c + d)}{2(h + t) \times length\ (mm)}$	This ratio is based on all four faces of the joist in the same way as kg3 and then this ratio is divided by the knot group length to create a ratio between knot diameters and surface area. To keep this ratio of the same magnitude as the others, it is also multiplied by 1000.

The results of this manipulation of the knot measures are tabulated in Table 5.13 below, based on a knot group length of 400mm. For the general case of timber with all four faces accessible, it is seen that the highest correlation (0.191) is obtained with kg3, by taking all knot data from all four faces and simply dividing the sum of the knot diameters by the perimeter of the cross section of the joist. Including the length over which the assessment takes place, to create the 'area ratio' of kg8, has no effect on the strength of the correlation and so is an additional step that can be avoided. The refinements of the knot group measures kg0, kg1 and kg2 serve only to reduce correlation with MoE in comparison with the simpler averaging used in kg3.

For the particular case of timber with the top face inaccessible, the knot ratios kg4 and kg7 have virtually the same correlations (0.179 and 0.180 respectively) for the knot group length of 400mm. As less information is available for the model in this case (three instead of four faces of knots measurements), it is logical that the correlation is weakened in comparison with kg3. The refinements of knot group measures kg5, and kg6 serve only to weaken the correlation of the simpler averaging used in kg4. Bearing in mind the small sample size and the possibility of over-fitting the data, it is considered that the simpler knot ratio measure of kg4 is preferred over the more refined kg7 knot ratio measure.

Table 5.13. Coefficients of determination between MoE and a variety of manipulations of knot group measures kg0 to kg8. Blue shaded cells show the less weak correlations.

	kg0	kg1	kg2	kg3	kg4	kg5	kg6	kg7	kg8
kg	0.150	0.151	0.169	0.191	0.179	0.118	0.155	0.180	0.191
1/kg	0.122	0.121	0.108	0.124	0.067	0.053	0.060	0.067	0.124
kg^2	0.104	0.105	0.128	0.146	0.136	0.076	0.113	0.137	0.146
$1/kg^2$	0.056	0.056	0.034	0.041	0.007	0.006	0.006	0.007	0.041
ln kg	0.167	0.167	0.176	0.195	0.170	0.127	0.152	0.171	0.195
1/ ln kg	0.005	0.000	0.002	0.002	0.035	0.007	0.009	0.001	0.006
ln (1/kg)	0.167	0.167	0.176	0.195	0.170	0.127	0.152	0.171	0.195
ln (kg^2)	0.099	0.132	0.109	0.159	0.119	0.070	0.017	0.036	0.073

The knot group measures kg3 and kg4 are identified previously as being promising for the prediction of MoE. Their coefficients of determination without any manipulation are 0.191 and 0.179 respectively. By taking the natural log of the knot group measures (ln kg), the coefficients of determination for kg3 is increased to 0.195 and that for kg4 is reduced to 0.170. This suggests that the knot group measure should not be further manipulated and it should be left in its raw state.

In summary, based on the sample in this study, the knot group measures with the highest coefficient of determination with MoE are:

(i) assessed over a length of around 400mm or longer
(ii) simple averages of the sum of knot diameters divided by perimeter length of the joist cross section over which the knot measures were taken
(iii) with no additional manipulation (e.g. natural log, inversion, etc.)

(iv) best measured, where possible, over all four faces.

As discussed above for knot clusters, knot group ratio measures will also be influenced by site inspection conditions and so further ratios are considered to review the effects of limiting the range of measurements available to a structural engineer on site. Table 5.14 describes four further knot group ratio measures relating to in situ scenarios and Table 5.15 presents the coefficients of determination with MoE.

Table 5.14. Knot group ratio measures suitable for some in situ scenarios

Reference	Formula	Comments
kg9	$\frac{a+c+d}{2h+t}$	This only considers the two vertical wide faces and the top narrow face. This could be considered to be the inverse of kg4.
kg10	$\frac{a+c}{2h}$	The sum of the two vertical faces divided by double the vertical height of the joist
kg11	$\frac{a}{h}$	The left vertical face of the joist divided by the vertical height of the joist
kg12	$\frac{c}{h}$	The right vertical face of the joist divided by the vertical height of the joist
kg11/12	$\frac{a}{h}$ and $\frac{c}{h}$ combined	Although theoretically possible to differentiate between the inner and outer vertical faces of a joist, this is not possible when only one face of the joist is visible. for a single vertical face, any correlations must be based on the combined inner and outer vertical faces.

Table 5.15. Coefficients of determination between various methods of calculating knot group ratios and MoE, for some in situ scenarios. Blue shaded cells show the less weak correlations.

Length (mm)	kg3	kg4	kg9	kg10	kg11/12
100	0.150	0.143	0.154	0.156	0.112
200	0.174	0.164	0.181	0.180	0.123
300	0.180	0.166	0.185	0.177	0.120
400	0.191	0.179	0.196	0.188	0.124
500	0.188	0.174	0.197	0.188	0.125

The ratio kg11/12 is based on the correlation of each vertical face (considered separately) with MoE. Two of the scenario based knot group ratios (kg9 and kg10) are seen to have similar coefficients of determination when compared with the ratio kg3 (based on all four sides of the test pieces). This is considered likely to be a quirk of the small sample set, as is the following for kg10. The ratio kg10 suggests a relatively strong correlation between the knot groups on the two vertical faces and MoE.

However, when each vertical face is taken separately (as is the case for the ratio kg11/12), then the correlation weakens.

5.3.1.5 Knots in zones

It is worthwhile to consider the effect of knots occurring in different regions of a joist, particularly when considering MoR. Knots near the base of a joist would be expected to have the greatest effect on MoR and those near the mid-height of a joist together with those above the mid-height centre line of the joist would be expected to have the least effect on MoR (due to the elastic distribution of bending stresses). Wood is considered to be weakened by the deviation of grain caused by knots and this is exacerbated at the cut face at the bottom edge of a joist by the discontinuity of grain exposed there.

In order to investigate this, four zones have been created and the coefficients of determination for the knots present in each of the four zones with MoR are determined. Additionally, some zones have been combined to extend this analysis a little further (many more variants were investigated but are not reported on here as the additional results do not affect the findings). The zones run from top to bottom of the joist, as shown in Figure 5.4.

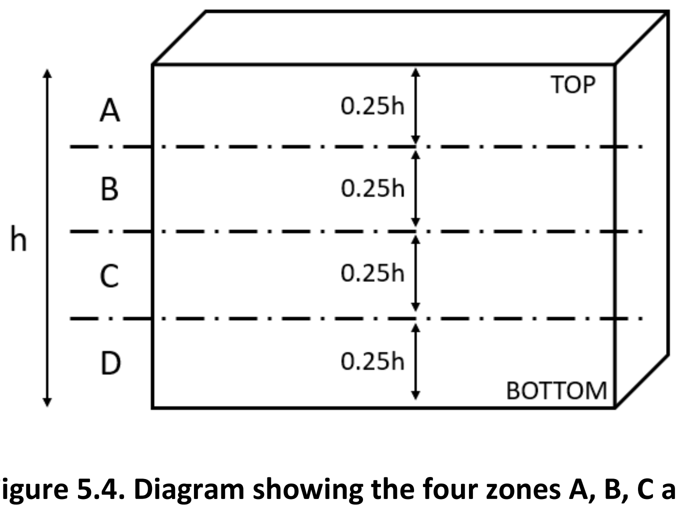

Figure 5.4. Diagram showing the four zones A, B, C and D in the wide vertical face of a joist

The numerical values directly beneath the letters in Table 5.16 refer to the distance from the top of the joist to the bottom of the 'zone' as a percentage (e.g. for a joist 100mm height, Zone A extends from the top to 25mm below the top). The knot ratio measures are a simple ratio of the knot cluster measure (on the two wide vertical faces) divided by combined height of the two vertical faces. The coefficients of determination are based on a knot cluster length of 300mm.

Table 5.16. Coefficients of determination between knot ratio measures (based on Zones A, B, C and D on the wide vertical faces of the joists) and MoR

A 0-25	B 25-50	C 50-75	D 75-100	ABCD 0-100	AB 0-50	CD 50-100	BC 25-75
0.087	0.033	0.056	0.111	0.176	0.090	0.128	0.065

Moving from top to bottom of the joist, it would be expected that Zones A and B would have little correlation with MoR, and that Zones C and D would have significant correlation. Additionally, the combined CD zone would be expected to have better correlation than the combined AB zone. It is noted that although these trends exist, they do so only weakly, indicating that knots in the lower half of joists correlate with MoR slightly less weakly than knots in the upper half of joists.

Two slightly stronger trends are noted. Firstly, that the outer Zones A and D have higher coefficients of determination (0.087 and 0.111) than the inner Zones B and C (0.033 and 0.056). As maximum compressive stresses in bending occur at the top of the joists and maximum tensile stresses in bending occur at the bottom of the joists, this suggests that the effect of knots on the tensile strength of timber may be complemented by their effect on compressive strength also.

This may partly explain the weakness of the elastic analysis approach described in this chapter. In that approach, the reduced elastic modulus of each joist is calculated based solely on knots occurring below the mid-height centre line of the joist. By omitting those knots in the top half of each joist, correlation with MoR reduces. Even having said that, it is still plainly not worthwhile pursuing the elastic section modulus model any further.

Secondly, the best performing 'zone' of all is that of ABCD, encompassing the full height of the joist, with a coefficient of determination of 0.176. This suggests that all knots are important, wherever they are located and that even though their relationship with MoR may not be directly causal, there is still correlation.

In the sub-sections above, the knot zone is extended to include both the top and bottom narrow face edges and it is seen that extending the zone within which knots are measured increases the coefficient of determination. From this sample of the minor species, the overall knot cluster measure of all four faces and over at least a minimum length of a joist gives the strongest correlations with MoR.

In summary, the two reasons relating to grain (given in the first paragraph of this section explaining how knots influence the bending strength of timber joists in bending) are seen to be weak. Rather, the unknown relationship between the total presence of knots within a joist and MoR leads to a stronger correlation than the seemingly rational ones offered. Additionally, for future versions of the predictive models, as the upper and lower zones (A and D) are those that are best correlated with MoR, then it may prove worthwhile to review further knot group ratio measures with greater weightings for these zones. This is not taken further in this study.

5.3.1.6 Knots as voids

Two sets of correlations were calculated (between the predicted strength reductions using the equations of ASTM D245 and measured MoR), firstly with single knots and secondly with knot clusters (extending over a length of 150mm). For further information on the backgrounds of these approaches and on the methods used by ASTM D245, reference should be made to the supplementary documents: "Technical note on the determination of strength reduction factors using elastic analysis" and "Technical note on the determination of strength reduction factors using ASTM D245".

The first set of correlations makes use of the plain equations of D245 and the second set makes use of the optional adjustment to these equations, using the 'tapering' of strength reduction values between centre and edge locations. A third set of correlations were made between strength predictions and measured MoR based on a more complex calculation (based on first principles) of the elastic section modulus of the cross section of the joists (assuming knots as voids). In Table 5.17, these correlations with bending strength are presented and extended to include MoE.

For a rectangular joist, bending strength is directly proportional to the elastic section modulus (z) and bending stiffness is directly proportional to the second moment of area (I). However, z and I are not directly proportional as $z \propto h^2$ and $I \propto h^3$. Thus, the relationship between MoR and MoE would not be expected to be perfectly linear (even though any trendline would be expected to be a gentle curve) and so correlations with MoE are expected to be weaker than with MoR. If promise were to be shown for MoE, then a more exact approach could be taken to determine second moments of area based on knots as voids.

Table 5.17. Coefficients of determination for relationships between MoR / MoE and strength reduction factors calculated using (i) 'plain' D245 equations, (ii) 'tapering' D245 equations and (iii) an analysis of the elastic section modulus of the joists following removal of knot areas below the centre line, assumed to be void

		MoR	MoE
D245 strength reduction	Single knots	0.113	0.157
	Knot clusters	0.119	0.132
D245 strength reduction with tapering	Single knots	0.127	0.158
	Knot clusters	0.132	0.132
Elastic section modulus from first principles	Single knots	0.095	0.040
	Knot clusters	0.109	0.047

Firstly, the method of calculating the strength reduction from first principles has a weaker correlation with both MoR and MoE than using either version of D245. It should be noted that all of these approaches assume both correlation and causation; joists become weaker due to loss of effective cross sectional area due to knots acting as voids. It would be expected that the more sophisticated assessment of strength reduction calculated from first principles would have a better correlation with MoR than the more basic D245 strength reduction estimates, which are based on gross assumptions regarding knot locations. This is not the case. As per the literature, the first principles method is based on reductions of the elastic section modulus considering only knots failing to transmit tensile forces below the neutral axis (it is assumed that knots above the neutral axis can transfer compression forces). So, one reason for the worse performance of the first principles method could be that the overall number and size of knots in a given length of joist (both above and below the neutral axis) is a better indicator of bending strength than any calculation based on the elastic section modulus (accounting only for those knots below the neutral axis). Thus, as D245 strength reduction includes knots both below and above the neutral axis (whereas the first principles method only considers knots below) it simply doubles the information in the model.

Additionally, it would be expected that both of these correlations would be higher than those that rely solely on surface knot ratios, knot cluster ratios or even knot group ratios. Again, this is not the case; the 'knots as voids' correlations with MoR in Table 5.17 vary from 0.095 to 0.132 and the knot ratio correlations (based on the ratio of knot diameters and joist dimensions) vary up to 0.191 as shown in Table 5.13.

Secondly, the effect on MoR and the effect on the apparent stiffness of the timber joists (i.e. the stiffness of the section remaining after removal of the voids due to knots) would be expected to be quite different. The supposed absence of material from several small discrete sections of a joist would be expected to affect bending stiffness locally but would not be expected to make such a significant effect over the entire length of a joist. In short, as knot voids increase locally, deflections would be expected to increase a little but not a lot. Thus, the relationships between knot voids and MoE would be expected to be significantly weaker than with MoR. This is not the case, as correlation coefficients for D245 strength reductions with MoR and MoE are almost the same. This could possibly be a function of the relatively small sample size but is firstly interpreted as an indication of the weakness of the 'knots as voids' correlations with MoR.

Thirdly, it is seen that the coefficients of determination in Table 5.17, particularly with MoR, are very weak and despite the complex calculations used, these are no better than the simple knot ratios used in the European codes of practice INSTA142 and DIN4074. Thus, in choosing the most appropriate knot measure for in situ timber assessment, it is not considered to be worthwhile continuing with the approach of considering knots as voids.

5.3.1.7 RoG and SoG and Density

Coefficients of determination were determined for RoG and SoG with the grade determining properties of the four minor species. For MoR, these values can be compared with the correlation coefficients of Table 5.2 at the start of this section and are seen to be similar.

Table 5.18. Correlation coefficients and coefficients of determination for the four minor species

	Correlation coefficients r					Coefficients of determination r^2				
	MoE	MoR	Dens	RoG	SoG	MoE	MoR	Dens	RoG	SoG
MoE	1	0.779	0.613	-0.699	-0.120	1	0.607	0.376	0.488	0.014
MoR		1	0.499	-0.473	-0.176		1	0.249	0.224	0.031
Dens			1	-0.470	-0.122			1	0.221	0.015
RoG				1	0.050				1	0.003
SoG					1					1

SoG is seen to have very weak correlations with both MoR and MoE and RoG has weak correlations, of a similar order to density. It is considered that SoG is unlikely to be able to contribute significantly to any predictive model.

5.3.1.8 The weakest, least stiff and least dense joists

As some timber joists may be of exceptionally low strength, stiffness or density, consideration is given to identifying any clear cut off points, based on visual grading parameters (plus density), that differentiate the very worst joists from the others. This is to reduce the risk that one or more of the weakest, least stiff and least dense joists could pass through the assessment process undetected.

The 60 weakest, least stiff and least dense joists were split into two groups of thirty (1-30 and 31-60) and their properties plotted on graphs against their SoG, RoG, density and knot ratio data. It was hoped that a pattern would emerge, leading to suitable cut off limits for one or more of the visual grading parameters.

Several graphs were created and the correlations between the properties and the visual grading parameters were seen to be weak or non-existent. To illustrate how disappointing the results are, just two graphs are reproduced in Figure 5.5 and Figure 5.6. It may be that a further statistical analysis could potentially show some significance between the two groups of thirty joists for one or more pairing; but this is not the point of this exercise. Rather, it is to search for distinct cut-off points separating the weakest, least stiff and least dense joists from the remaining joists with poor mechanical and physical properties.

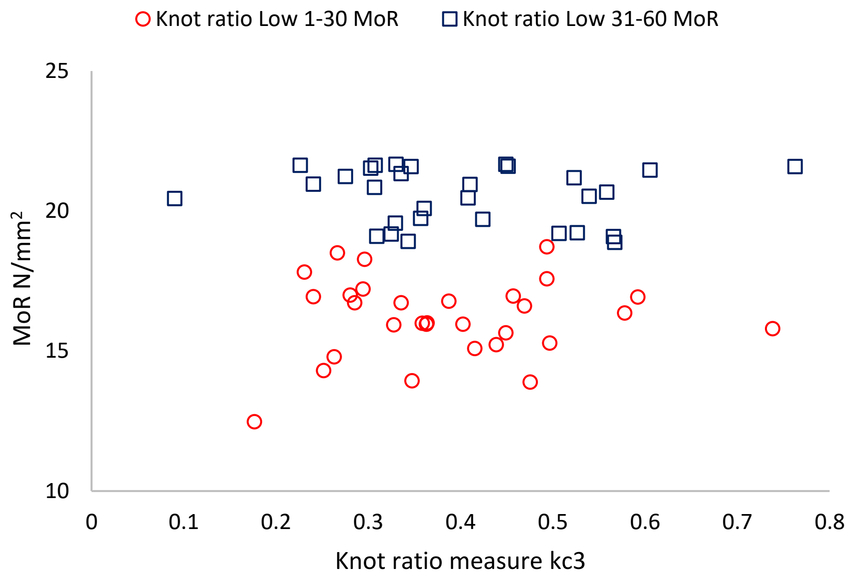

Figure 5.5. Graph showing MoR and kc3 for weakest test pieces

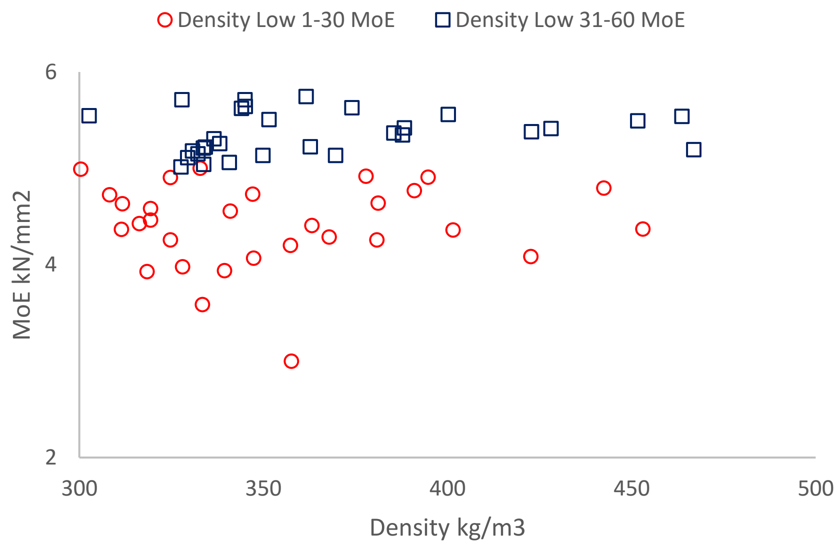

Figure 5.6. Graphs showing MoE and density for least stiff test pieces

Nevertheless, it may be worthwhile to introduce interim cut off points for predictor variables in a similar way to the visual grading codes as the minor species sample contained very few extreme measurements, possibly due to the reasons given in Chapter 7 regarding sorting of timber joists for laboratory testing. Table 5.19 is compiled from the review carried out in Chapter 4, and the worst case values of knot measures and SoG are suggested as interim cut off values for the predictive models.

Table 5.19. Minimum values of knots and SoG in visual grading codes

	INSTA142	DIN4074	BS4978	Cut off for model
Horizontal narrow edge limits for knots as a percentage of edge dimension (b)	100	60	100	100
Vertical wide face limits for knots as a percentage of face dimension (h)	50	60	50	60
Slope of grain (as deviation in mm over 100 mm length)	25	12	17	25

The cut off values for the model are illustrated in Figure 5.7. None of the minor species test pieces exceed either the SoG or the knot limits proposed and only four joists have wide face knots greater than 50% of the wide face dimension.

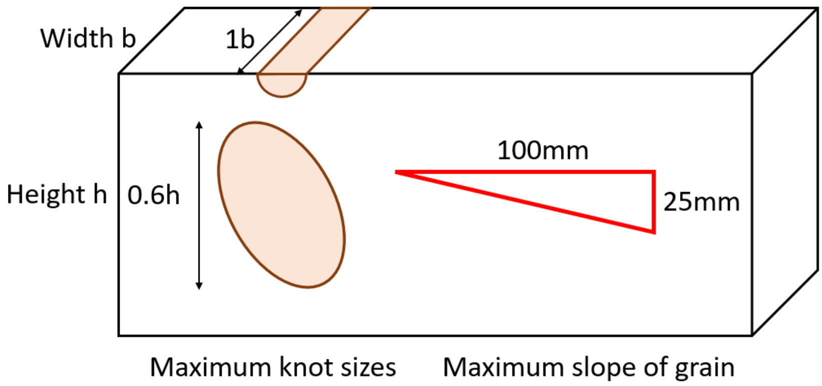

Figure 5.7. Limits of knot sizes and slope of grain for use in the model

5.3.1.9 Relationship to pith and wane

As the logs in this study were cut to obtain the maximum yield of test pieces (within the limits of the prescribed cutting pattern), the outermost joists from any given log are expected to be from near the outer edge of the log , even though they may not necessarily reveal bark or rounded arises (i.e. wane). The 5-percentile values of MoR and density were determined non-parametrically and are presented in Table 5.20 along with the mean and interquartile values of MoE for both outermost joists and inner joists.

Table 5.20. Mean values and interquartile and 5-percentile values (determined non-parametrically) of outermost and inner joists

	Outermost Joists	Inner Joists
	Q3 Interquartile value	
MoR (N/mm^2)	50.0	38.6
MoE (kN/mm^2)	10.8	8.8
Density (kg/m^3)	451	422
	Mean values	
MoR (N/mm^2)	41.5	32.2
MoE (kN/mm^2)	9.4	7.6
Density (kg/m^3)	418	395
	Q1 Interquartile value	
MoR (N/mm^2)	32.3	24.2
MoE (kN/mm^2)	8.0	6.3
Density (kg/m^3)	380	362
	5-percentile values	
MoR (N/mm^2)	21.5	16.9
MoE (kN/mm^2)	6.7	4.6
Density (kg/m^3)	337	327

The mean values in Table 5.20 suggest that the mechanical and physical properties of the outermost joists are superior to those of the inner joists. Importantly, the 5-percentile values of MoR and the mean of MoE show large differences between the outermost and inner joists; additionally, the 5-percentile values of density show a modest difference.

Reference should also be made to the box and whisker plots in Figure 5.8. These show the interquartile points, mean (shown as a cross) and outliers (outside the interquartile range by more than 1.5 x the interquartile range, shown as hollow dots). For MoR, Q1 of the outermost joists is greater than the median of the inner joists. For MoE, Q1 of the outermost joists is greater than all of the inner joists. For density, the median of the outermost joists is greater than Q3 of the inner joists (however, the mean of the outermost joists is a little less than the Q3 of the inner joists). This confirms the superior mechanical and physical properties of the outermost joists in the sample.

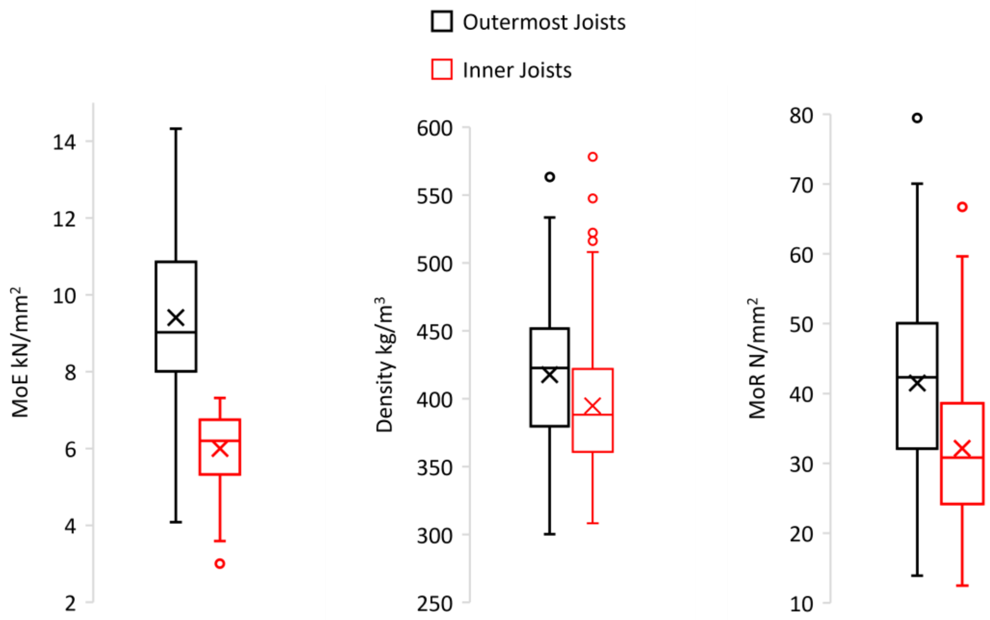

Figure 5.8. Box and whisker plots of MoE, density and MoR for inner and outer joists

Thus, the presence of wane, which is a clear indicator of an "outermost" timber element, is likely to be indicative of improved (rather than worsened) mechanical and physical properties (it could, however, simply relate to a log cut from a young tree or from near the top of an old tree, in which case, it would be accompanied by juvenile wood). Whilst in visually grading a package of newly cut timber elements, it is reasonable to reject those elements with significant wane in order to rationalise and improve the saleability of the lot, for in situ timber, wane is no reason to reject or mark down the mechanical and physical properties of a timber element; based on these results, it is the opposite. The economics of repair and refurbishment work are such that it is likely to be worthwhile carrying out additional structural calculations to account for section loss due to wane; something which would be highly unlikely for new timber in new build. Also, the presence of significant wane (which is tightly restricted in modern timber grading) is a marker of the age of a timber element and may be valued as such and considered attractive and particularly worthwhile saving.

Incidentally, loss of section due to other courses (such as fungal or insect damage) could be accepted and treated in a similar way, i.e. accounting for it in structural calculations. Finally, just because wane is an indicator of better timber in this study, does not mean this is always the case for in situ timber. A load of timber joists, sorted and delivered to a construction site could include inner joists from some trees and outer joists from others.

5.4 Conclusions

The purpose of this chapter is to determine the best visual features to use in the predictive model. This is not just a question of what should be included but how. Knots are a key feature and can be measured and recorded in many ways and so many questions needed answering:

1. Which is the best or are the better measures: single knots, knot clusters and knot groups?
2. For knot clusters and knot groups, what length should be used?
3. Which knot measure ratios are the best and should these be manipulated by for instance inverting or squaring?
4. Can knots be treated in structural calculations as voids to determine reduced section properties?
5. From top to bottom of a joist, are knots in some zones more important than others?

Based on the limited sample of this study, knot clusters over lengths of 300mm or longer have the strongest (or rather least weak) correlations with MoR. Additionally, knot groups over lengths of 400mm or longer have the strongest (or least weak) correlations with MoE. For both mechanical properties, the best knot measures use all four longitudinal faces of the joist and simple ratios (e.g. the sum of knot clusters divided by perimeter length of the joist cross section over which the knot measures are taken). It is possible that some additional manipulation can improve the correlation of knot clusters with MoR (i.e. natural log).

The development of these flexible knot measures (with the strongest relationships with the mechanical properties of individual joists) is a unique contribution to knowledge.

The outcomes of the comparison of knot measures based on knots as voids and based on the zoning of joists from top to bottom are demonstrated to be poor. This is shown by the very weak correlations between the measures based on knots acting as voids with both MoR and MoE. Simply adding up knot areas on all four sides of a joist gives stronger correlations. The brief investigation into vertical zoning of knots shows that lower zones are more important than upper ones, and that more zones are better still. So, the best predictive model will include all four faces of a joist but other, slightly weaker models can use three or two faces. The demonstration of the weakness of the relationships between knot measures based on knots as voids and the mechanical properties of individual joists is a unique contribution to knowledge.

In this study, wane, which is used in visual grading codes as a grade limiting feature, is seen to be associated with superior timber close to the outside of the tree. It is a good indicator of timber that is typically better than that closer to the pith. On this basis, wane should be allowed in a predictive model but accounted for where reduction in cross section of joists is significant.

Correlations of both MoR and MoE with SoG are very weak and suggest that this could be omitted from a model with little loss, however, in those circumstances where very little information can be gained about an in situ joist, it could be worthwhile to include SoG in a predictive model. Correlations of both MoR and MoE with RoG are weak and as it is unlikely to be practicable to measure RoG for in situ structural timber, it is even less likely to be included in a predictive model.

Having now considered visual grading parameters in relation to the creation of predictive models, the next chapter considers NDT and SDT ones.

Chapter 6 NDT and SDT grading parameters

6.1 Introduction

The purpose of this chapter is to understand the range of testing techniques practicably available for the appraisal of the mechanical and physical properties of in situ timber elements. It considers the effectiveness, advantages and disadvantages of NDT, SDT and combining NDT with SDT. Visual grading is a form of NDT and is covered in Chapter 4 and the more detailed consideration of each visual grading parameter is covered in Chapter 5. Finally, the combination of visual grading with other NDT or SDT techniques is covered in this chapter. This is followed by an overview of the manner in which NDT and SDT are used in practice and how they could be used more effectively. Before finally concluding the literature review, there is a brief discussion of the shortcomings of current research into old timber using SDT and NDT, and species independent strength grading.

6.2 Literature review

6.2.1 Introduction to literature review

In order to develop a model for the prediction of the mechanical and physical properties of in situ timber, those in situ measurements that can practicably be taken must be assessed for their potential usefulness. Table 6.1 provides an overview of the range of methods available for the appraisal of the mechanical and physical properties of in situ timber (ratings in order of usefulness are: Yes, Estimate, Limited). Additionally, each measurement can potentially be combined with others to improve predictions. The most relevant methods are reviewed in the following pages.

Table 6.1. Effectiveness of NDT and SDT to assess structural timber, adapted from (Riggio *et al.*, 2014)

Method	Effectiveness for strength	Effectiveness for stiffness	Effectiveness
Visual inspection			Limited A
Electrical methods for moisture content			Yes
Species identification with naked eye or microscope			Yes
Stress waves	Limited	Estimate	Limited A, B
Core drilling	Estimate	Estimate	Yes, A
Tension micro-specimens	Estimate	Estimate	
Resistance drilling	Limited		Yes A, B
Screw withdrawal	Limited		Limited A
Needle penetration	Limited		Limited A
Pin pushing	Estimate		Yes A, B
Surface hardness	Limited		Limited A
Digital radioscopy			Yes A, C Limited B
Ground penetrating radar			Limited A, C

A Locate deterioration; B Quantify deterioration; C Identify hidden details

As an illustration of some relationships between variables, coefficients of determination for a range of variables with the three key mechanical and physical properties are given in Table 6.2. The three measurements of MoR, MoE and density, in the table, have been carried out by testing to destruction in the laboratory, which is not an option for in situ timber. Alternatives to these include weighing the whole test piece and to use MoE_{dyn} , which is only indirectly related to actual MoE which in turn is also indirectly related to bending strength, MoR.

The coefficient of determination, r^2, for NDT with the key mechanical and physical properties of bending strength, stiffness and density are seen to vary by species and by study (Feio and Machado, 2015). Values for spruce and Scots pine from the Combigrade Project are presented in Table 2.5. Values from the Gradewood Project are shown in Table 6.2 (n=2776 except for MoE_{dyn} measured by ultrasonic time of flight, n=1612).

Table 6.2. Coefficients of determination of NDT with mechanical and physical properties of spruce and Scots pine (Ranta-Maunus, Denzler and Stapel, 2011, p. 21, p.28). Pink shaded cells are of particular interest.

	Coefficient of determination, r^2 spruce			Coefficient of determination, r^2 Scots pine		
	MoR	MoE	Density	MoR	MoE	Density
MoR (measured destructively)	1	0.66	0.28	1	0.53	0.21
MoE (measured destructively)	0.66	1	0.54	0.53	1	0.54
Density (measured destructively)	0.28	0.54	1	0.21	0.54	1
Density (whole test piece, measured and weighed)	0.25	0.50	0.94	0.21	0.57	0.89
MoE_{dyn} based on natural frequency and notional density	0.51	0.68	0.23	0.46	0.60	0.14
MoE_{dyn} based on natural frequency and measured density	0.54	0.83	0.66	0.50	0.85	0.54
MoE_{dyn} based on ultrasonic time of flight	0.40	0.70	0.66	0.44	0.75	0.54
Knot area ratio	0.31	0.21	0.06	0.40	0.25	0.09

Table 6.2 illustrates the very weak or weak correlations between knot area ratio and all three of the mechanical and physical properties (cells shaded pink), suggesting that this, the best of all the visual grading predictors, may be of only some limited potential use with MoR and MoE and of no use with density.

A strong correlation is indicative of one variable potentially being a good predictor of the other and when considering the prediction of MoE for both species, all three versions of MoE_{dyn} have moderate to strong correlations, with MoE_{dyn} based on natural frequency and measured density being the strongest (and shaded pink). When considering the prediction of MoR for both species, measured MoE has the strongest correlation and failing this, the moderate correlation with MoE_{dyn} based on natural frequency and measured density is the best.

Tests on in situ timber can roughly be divided into studies of the condition of the wood (the location, size and extent of defects) and studies of its mechanical and physical properties. The focus of this literature review is on the mechanical and physical properties.

6.2.2 Non-destructive testing (NDT) and semi-destructive testing (SDT)

6.2.2.1 Visual inspection

Briefly, it is worth pointing out that all sources recommend a visual inspection to form an early part of any investigation. A visual inspection of structural timber needs to encompass: (i) dimensions, (ii) possible wood decay, (iii) visible mechanical damage, (iv) evidence of past moisture intrusion issues. The visual inspection is essential to allow the structural engineer to plan further investigation, possibly in the form of sampling or testing (Riggio *et al.*, 2014). It also allows the structural engineer to make an initial subjective judgement of the structure, which can be most useful, but is of limited use in determining the mechanical and physical properties of the timber in question.

6.2.2.2 Moisture content

The moisture content of situ timber is needed to calibrate test results with standardised formulae and data. It is also needed to assess the condition of the wood and its risk of insect and fungal attack. As moisture content can vary along the length of a timber element, it is useful to measure moisture content at several locations (Riggio *et al.*, 2014). The standard laboratory test for moisture content of a test piece in the Eurocodes is based on a single, full cross section, block of wood cut from the test piece (for wood used in a destructive bending test, to be sited as close as possible to the key position of failure). The block must be of clear wood, free from resin pockets and knots (CEN, 2003a, 2012b). The moisture content is found using the oven dry method. The same block is also used to give the density of the test piece.

The results of bending tests are subsequently calibrated using the oven dry moisture content of the clear wood block. Thus, the standard moisture content and density from laboratory tests is based on a single location of clear wood, even though, along the length of the test piece, values of density are likely to vary (especially at locations of knots, wane, fissures, resin pockets, etc.) and for in situ timber, moisture content could also vary depending on distance from external walls and other potential sources of moisture.

The electrical resistance method of assessing moisture content is similar to the electrical conductance method in that it measures electrical properties of wood that vary in a predictable way with changing moisture content, even though correlations are not perfect and care must be taken in carrying out the necessary measurements. Results are reliably rapid and accurate (Riggio *et al.*, 2014) and both electrical methods are routinely used in the construction industry. So, it is seen that the moisture content of in situ timber can be reliably, quickly and cheaply measured.

6.2.2.3 Species Identification

Some wood species (with easily identifiable characteristics) can be identified using the naked eye or a hand lens (with magnification of around x7 to x10) focussing on, for instance, colour and texture. If this is not possible then the species can be assessed through taking a small sample and examining a prepared specimen under a microscope (Hoadley, 1990). Both steps are typically beyond the ability of a structural engineer and so samples are sent away to a specialist service to carry out the species identification.

Microscopic examination uses a key system to identify order, family and genus of a specimen. Having sent a specimen for specialist examination, a report is produced with method of identification, anatomical characteristics, scientific and common names (Riggio *et al.*, 2014). Identifications based on anatomy are generally accurate only to genus or subgeneric grouping. There are over one hundred pine species alone and so, any method of assessment of the mechanical and physical properties of in situ timber that relies on the knowledge of species may have difficulties in allotting specific species to specimens and in any case, will be relatively more expensive and time consuming than a method that is not species dependent.

6.2.2.4 Ultrasonic and acoustic (stress wave) tests

Ultrasonic and acoustic (stress wave) tests are similar tests that measure the time taken for compression waves to propagate through wood to estimate the dynamic modulus of elasticity, MoE_{dyn}. Ultrasonic tests use frequencies higher than the audible range and acoustic tests use sound waves. Piezoelectric sensors, located at a measured distance from each other and fixed to a timber element, can be used to measure the start time of an impulse (at one sensor) and its end time, after it propagates to the other sensor; giving the time of flight. Radial time of flight, across growth rings, differs to longitudinal time of flight, parallel to the grain of the wood, and, for a typical timber beam, the longitudinal time of flight would be measured for the prediction of mechanical properties. Knowledge of the species, moisture content and density are used to calibrate readings to estimate both stiffness and density.

The speed at which a stress wave travels along the length of a timber element is strongly dependent on MoE and density and weakly dependent on Poisson's ratio, so, any formula for MoE_{dyn} should account for the effect of Poisson's ratio. However, several researchers have found that the effects of Poisson's ratio are small and a simplified formula works well enough for typically sized timber joists; this is the formula that is commonly used (Kasal, Lear and Tannert, 2010):

$$MoE_{dyn} = \rho V^2 \qquad (6.1)$$

MoE_{dyn} is dynamic modulus of elasticity (N/mm^2), ρ is density (kg/m^3) and V is the propagation velocity of the longitudinal stress waves (m/s).

Estimates of mechanical and physical properties using measured density are better than those based on assumed density and, as in situ density measurements may be based on localised estimations of density (e.g. using cored samples), these should be taken at several locations to better estimate the global density of the element for incorporation into the predictive model. In the absence of a measured value of density, tabulated values of density for different species are used (Piazza and Riggio, 2008).

There is discussion as to the influence of length of test piece and accuracy of time of flight measurements which is somewhat dealt with in a recent study by Arriaga *et al.* (2019), finding that, under laboratory conditions, the differences between velocities differ by less than 4.5%. Here is an additional source of variation to be accounted for by any predictive model.

Some grading machines measure the resonant frequency of pieces of timber without their density (Ranta-Maunus, Denzler and Stapel, 2011). This reduces the complexity of the grading operation at the price of an increased degree of approximation and overall is acceptable to the industry, even though, including density would increase accuracy.

The natural frequency measurement of the first resonance frequency in longitudinal vibration is combined with the actual density of the test piece to determine the dynamic modulus of elasticity

$$MoE_{dyn} = (2\, x\, frequency\, x\, L)^2\, \rho_{test\ piece} \tag{6.2}$$

Where, L is the length of the test piece and $\rho_{testpiece}$ is the density of the test piece and $frequency$ is the first acoustic resonance frequency (Ranta-Maunus, Denzler and Stapel, 2011, p. 14).

Generally, the static modulus of elasticity is determined from the dynamic version using a linear equation:

$$MoE_{static} = \alpha\, MoE_{dyn} + \beta \tag{6.3}$$

α and β are species dependent constants

For the determination of MoE_{dyn} , flexural and longitudinal vibration tests (i.e. dynamic resonance), along with stress wave time of flight tests are the most common NDTs used (Cavalli and Togni, 2013), with stress wave methods (time of flight) being the most used in practice (for the estimation of both MoE_{dyn} and MoR) due to their speed and ease of use and acceptable level of precision (Kasal, Lear and Tannert, 2010; Feio and Machado, 2015).

It is reported that the dynamic natural frequency of a timber element can be measured in situ (despite it forming a part of a wider structural system) and be used to estimate the MoE of the element. A vibration sensor, mounted on the timber element in question, measures its frequency following the inducement of vibrations by for instance dropping a sandbag, or a person jumping and landing heavily. This gives a good approximation of MoE_{dyn} and subsequently static MoE (CEN, 2019b).

The results of studies comparing the dynamic resonance method with the time of fight method are mixed. Rohanova *et al*. (2010) compared two commercially available devices (Sylvatest Duo and MTG Timber Grader), using 52 structural sized spruce test pieces and found the dynamic resonance (MTG Timber Grader) to be the more reliable. However, the time of flight (Sylvatest Duo) device functioned consistently and reliably well once adjustments based on density and the outcomes of the laboratory load tests were included. Whereas, Vega *et al*. (Vega *et al.*, 2012) calculated almost identical coefficients of determination when both methods (ultrasonic and acoustic time of flight) were related to the global modulus of elasticity of 374 structural sized pieces of chestnut.

A summary of previous research outcomes is presented in Table 6.3 which shows strong and very strong correlations between values of MoE obtained from static bending and MoE_{dyn} obtained using the time of flight stress wave method. Pink shaded cells show results excluding non-structural sized specimens and those specimens not tested in bending. For these other categories (not shaded), correlations are typically even stronger.

Table 6.3. Summary of correlations between stress wave time of flight MoE and static bending MoE values, obtained from seven studies (Ross and Pellerin, 1994, p. 13)

Material	Static loading mode	Correlation coefficient, r	Coefficient of determination, r^2
Clear wood	Compression	0.98	0.96
Clear wood	Bending	0.98	0.96
Lumber	Bending	0.96	0.92
Veneer	Tension	0.94 – 0.96	0.88 – 0.92
Lumber	Bending	0.90 – 0.92	0.81 – 0.85
Lumber	Bending	0.96	0.92
Veneer	Tension	0.96	0.92
Veneer	Tension	0.99	0.98
Knotty lumber	Bending	0.87	0.76
Clear lumber	Bending	0.95	0.90

Factors that affect the propagation of stress waves through timber include frequency of the wave, material condition, size and location of defects, and the high attenuation that naturally occurs in the material of wood. Unfortunately, although high frequency transmissions are the most sensitive to internal defects, they also suffer greater attenuation than low frequency transmissions and so a balance must be struck between the sensitivity and the scope of each investigation.

Ultrasonic stress waves, have higher frequency and shorter wavelengths than acoustic ones, and so could be expected to be most affected by internal defects within timber elements (such as decay or knots or fissures) and so be found to be better predictors of MoR. However, this was not found to be the case by Vega *et al.* (2012) and remains to be demonstrated.

Additional factors that have been identified as affecting attenuation measurements include the geometry of the specimen, the relative densities of its earlywood and latewood cells, the lengths of the cells and the nature of the amorphous matrix in which they are embedded (Bucur and Bohnke, 1994). Ring orientation, moisture content, temperature, loading stresses within the timber element can also affect stress wave velocity and attenuation and ideally should be controlled for during investigations (Kasal, Lear and Tannert, 2010). Also, the length over which time of flight readings are taken affect the 'apparent' speed of a stress wave and need accounting for in calculating MoE_{dyn} (Llana *et al.*, 2016). Finally, it should be noted that a time of flight test is typically carried out over an extended length of a timber element whereas the measurement of stiffness, by testing to destruction in accordance with EN408, focusses on a short section containing ‘worst case defects’. Thus, the time of flight MoE_{dyn} reflects a longer length of a timber element than that which is tested as part of establishing the usual grading process and so further adjustment is recommended by Rais and Van de Kuilen (2015).

As is shown above, MoE_{dyn} can be found straightforwardly using the stress wave technique and a strong relationship between MoE_{dyn} and static MoE has been established empirically (as shown in Table 6.2), but no such direct relationship exists between MoE_{dyn} and MoR, and so the long established relationship between static MoE and MoR is employed to allow this mechanical property to be determined using stress waves. The strength of the relationship between MoE and MoR is discussed in Chapter 2 and is typically found to be moderate.

One reason for the strong relationship between static MoE and stress wave testing results is that both stress waves and static MoE are most affected by the clear wood properties of a timber element rather than by intermittent features (such as knots, local deviations in slope of grain or resin pockets) present along the length of the element (Kasal, Lear and Tannert, 2010). One suggested reason for the weaker relationship between MoR and stress wave testing results (either acoustic or ultrasonic) is that firstly, MoR can be strongly affected by intermittent features that weaken a timber element (particularly if these features occur at a location of high stress, such as close to the bottom edge, at the mid-span of a joist in bending) and secondly, stress wave testing results are poor at identifying these very same intermittent features, particularly if they are small in relation to the wavelength of the stress waves (Feio and Machado, 2015).

If this is true, then, for the prediction of MoR, it is important to combine stress wave testing with another form of testing that can measure these intermittent features. As almost all knots within a timber element appear on its surface, and generally three faces of an in situ element are available for inspection (Williams, 2009), then visual assessment is seen to be particularly suitable for this task. This could measure and record the estimated size and location of all strength reducing features for possible future combination with the results of the stress wave testing.

6.2.2.5 Small specimens taken in situ and tested in a laboratory

As discussed elsewhere, the density of structural sized joists is measured in the laboratory in accordance with EN408 (CEN, 2012b) and is based on a clear wood section cut from the test piece, and as such may not be the same as the density of the whole test piece. The correlation of this density with that of the entire test piece may only be moderate to strong. Bather *et al.* (2016) found a coefficient of determination of 0.74 when investigating 150 structural sized test pieces of western hemlock (*Tsuga heterophylla*). From the same study, a similar coefficient of determination of 0.70 was calculated for the relationship between the density of the clear wood section and two micro clear cored specimens, 6.5mm diameter, taken from the same test piece.

Other studies have reported similar results as is shown in Table 6.2. The unweighted average coefficient of determination is 0.79, showing strong correlation.

Table 6.4. Coefficients of determination from four studies on density

Study	Species	Coefficient of determination, r^2	Notes
A	Western hemlock (*Tsuga heterophylla*)	0.74	Longitudinal core, 6.5mm diameter
B	Norway spruce (*Picea abies*)	0.94	Lab weighing by scale
B	Norway spruce (*Picea abies*)	0.86	Grading machine IP
B	Scots pine (*Pinus sylvestris*)	0.89	Lab weighing by scale
B	Scots pine (*Pinus sylvestris*)	0.82	Grading machine IP
C	radiata pine (*Pinus radiata*)	0.8	Tangential core, 10mm and 16mm diameters
C	radiata pine (*Pinus radiata*)	0.8	Radial core, 10mm and 16mm diameters
D	Silver fir (*Abies alba*)	0.64	
D	Norway spruce (*Picea abies*)	0.89	
D	Pinus pinaster (*Pinus pinaster*)	0.48	

A ((Bather, Ridley-Ellis and Gil-Moreno, 2016)); B (Ranta-Maunus, Denzler and Stapel, 2011); C (Iniguez-Gonzalez *et al.*, 2015); D (Feio and Machado, 2015)

The usual NDT and SDT methods of measuring density include: (i) needle penetration resistance, (ii) screw withdrawal resistance, (iii) core drilling (as described in this section) and (iv) drilling chips extraction (DCE). The final method, DCE, is less well known than the others but performs well on structural sized test pieces, showing very strong correlation with density, with a coefficient of determination of 0.93 for a small range of softwood species (Martínez *et al.*, 2020). A study by Llana *et al*. (2018) ranked the efficacy of these methods on in situ timber with core drilling being best (the larger the core, the better), followed by DCE, with needle penetration resistance and screw withdrawal resistance, being significantly worse performers than the two SDT methods that create moderately sized holes in timber elements. Interestingly, Martinez's study found there to be no statistically significant difference between DCE applied radially or tangentially to a test piece. Consequently, and most usefully, this method can be applied in situ without knowledge of the orientation of the radial and tangential axes, which is almost always the case in practice. Finally, the Martinez study included five different softwood species and no significant differences relating to species were identified. In fact, the OLS regression model developed also included hardwood species. So, at this stage, there is no apparent reason to consider sample selection issues relating to species and density.

The study of cores and density by Bather *et al*. (2016) was extended to test the longitudinal cores in bending to destruction (over a span of 78mm), thereby allowing comparison of MoE and MoR of the cores with the structural sized joists, from which they were cut. Two cores from each joist were tested in this way and their averaged results give coefficients of determination, r^2, with MoR and MoE of 0.27 and 0.61, respectively. Neither of these results were as high as for MoE_{dyn} measured using dynamic resonance which gave coefficients of determination of 0.5 and 0.9, respectively.

For the estimation of tensile strength, the use of very small specimens of clear wood taken from in situ timber and tested in the laboratory has yielded mixed results, depending on the size of the test piece cut from the timber element. The smaller straight sided clear wood specimens which are relatively easy to extract from a timber element in situ are difficult to test in the laboratory. The coefficients of determination, r^2, between small specimens and standard sized test pieces from one study (Maritime pine (n=25) and chestnut (n=25) are given in Table 6.5.

Table 6.5. Coefficients of determination, r^2, between testing small specimens and standard sized specimens in tension (Brites, Lourenco and Saporiti Machado, 2012)

	MoE	Tension
Maritime pine	0.53	0.25
Chestnut	0.67	0.45
Combined results	0.75	0.5

Tensile tests carried out on small specimens taken from in situ timber elements have proved sensitive to the slope of grain and the ratio of earlywood and latewood. Additionally, as the specimens are typically sawn from an outer corner of an existing timber element, the wood of the test piece is not representative of the wood in the element (Kloiber *et al.*, 2015) and so it is recommended that several specimens are taken and that they are as large as possible, which increases the impact that the investigative works have on the existing structure. If sufficiently large enough specimens are cut from the in situ timber, their test results should be no different to those of specimens cut in the normal manner. Even with multiple specimens, the issue remains regarding the position in the cross section from where the small specimens are taken. In studies, this has been one corner of the in situ element and so could comprise wood, not representative of the element as a whole (e.g. specimens from a boxed heart joist could be mature wood while the majority of the element could be juvenile wood).

Additionally, radial cores of wood around 5mm diameter have been taken from in situ timber elements and tested in compression and the correlation coefficient of their relationship with compressive strength parallel to the grain have been found to range between 0.77 and 0.96 (Kloiber *et al.*, 2015). This research found similarly strong relationships with the compression test results and both density and MoE parallel to the grain.

These relationships are surprisingly strong, as accepted and published correlation coefficients for the relationships between radial compressive strength and say compressive strength parallel to the grain (r = 0.6) or MoE parallel to the grain (r = 0.4) are significantly lower (Joint Committee on Structural Safety, 2000). It should also be borne in mind that these weaker relationships are based on multiple studies, including ones of structural sized test pieces.

Taking and processing a cored sample is costly and, due to its semi destructive nature, the number of specimens is limited to reduce damage to the existing structure and so may not be wholly representative. However, the minimal impact of these cores and their effective use to accurately assess density of wood is clear (Kasal, Lear and Tannert, 2010). What is less clear is the reliability of the predictive power of other tests on small specimens cut from in situ timber elements. More testing is needed to confirm their effectiveness, particularly for MoE and MoR.

6.2.2.6 Load testing in situ

This can be used to provide a reliable 'final' method of determining the strength and stiffness of a timber element in situ. This method is commonly used for new timber bridges in some countries (e.g. Slovenia). Load testing can globally assess a timber structure (providing approximate general results) and, if it is possible to isolate an element, can be used on an individual member (providing exact results). It is expensive and time consuming (Dietsch and Kohler, 2010) and carries the risk of failure of in situ elements. Overall, its expense is such that it is rarely used, even in heritage buildings, to say nothing of structures of lower intrinsic value.

6.2.2.7 Sclerometer testing and resistance drilling

For the determination of density, screw withdrawal, surface hardness testing (e.g. Pilodyn®) and drill resistance are the most common NDTs used (Cavalli and Togni, 2013) and are the subject of many academic papers. A sclerometer test is a dynamic hardness test, like the more widely known rebound test used to measure the hardness of concrete. The most commonly used commercial device is the Pilodyn® which shoots a 2.5mm diameter steel rod and measures the response (embedment depth of the steel pin).

The Pilodyn® method has been compared with (i) screw withdrawal force (see next sub-section) and (ii) transversal stress wave velocity. Using small samples of known species and combining tangential and radial readings, these methods can achieve coefficients of determination, r^2, of 0.61, 0.67 and 0.34 respectively (Iniguez *et al.*, 2010). Unfortunately, the application of these methods in practice can be problematic due to irregularities and local deterioration (especially of the surface) of existing in situ timber and lack of knowledge of species and the need to apply a different predictive model for each species.

The indentation test method used in the sclerometer test can be performed slightly differently, for instance, the modified Janka test measures the force required to indent an 11.28mm diameter steel ball to 5.64mm (its radius). This test has also been used as a basis for the prediction of MoE and in one study its coefficient of determination was found to be $r^2 = 0.36$ (Piazza and Riggio, 2008). Further drawbacks of this test include low resolution of readings, limitation to testing the surface of timber elements, inability to complete the test on wood that is relatively hard and finally, the test is heavily dependent on the angle between the grain of the wood and the direction of penetration. This final point relates to the sclerometer testing also.

Resistance drills use small diameter needle-like drills, with oversized heads (to avoid friction along the shaft of the drill) to bore into timber elements and to measure the resistance encountered. They are commonly used to determine the extent of wood degraded by fungal attack and are particularly useful for timber embedded in walls, where drilling at 45° to the face of the timber element allows penetration beyond the face of the wall. They are also useful to map the extent of suspected internal pockets of degraded wood (due to fungal attack) or cavities within timber elements.

Unfortunately, the extreme variability of the resistance of wood to the penetration of the drill bit, reduces the effectiveness of this technique (both between species and within species) and even the relatively simple task of assessing the presence of cavities within a timber element can be confused by natural and ‘harmless’ wood features (CEN, 2019b).

The advantage of resistance drilling over sclerometer testing is that it can penetrate the full cross section of a timber element and thus gives an approximate measure of the mean density across the section. The sclerometer measure is limited to the surface of the timber element and the surface density may differ from internal density due to differences in wood (e.g. juvenile and mature wood) and differences in degradation from biological or insect attack). The advantage of sclerometer testing over resistance drilling is that it is less damaging to the timber element. It is also useful as a quick measure of the surface degradation of timber elements (Ross and Pellerin, 1994).

Resistance drilling (using the proprietary Resistograph® drill) and sclerometer testing (using the proprietary Pilodyn®) are used in several studies to determine the density of in situ elements. In one study, as Table 6.6 shows, coefficients of determination, r^2, for density can be strong and for compressive strength can be moderate. Similarly strong coefficients of determination, r^2, for sclerometer testing with density were also found by Gorlacher (1987), ranging from 0.74 to 0.92 (partly achieved through taking a large number of measurements).

Table 6.6. Coefficients of determination, r^2, between resistance drilling and sclerometer testing and density and compressive strength (Henriques *et al.*, 2011) (*Pinus sylvestris* (n=64) and *Pinus pinaster* (n=82))

	Density	Compressive strength
Resistograph®	0.87	0.70
Pilodyn®	0.80	0.61
Density		0.75

Other studies have found a wide range in the strength of the relationship between resistance drilling measures and mechanical and physical properties. Feio *et al*. (2005) obtained moderate and strong coefficients of determination, r^2, for the relationship between resistance drilling measures and the MoE, density and compression strength of chestnut test pieces (ranging from $r^2 = 0.59$ to 0.70). Piazza and Riggio (2008) found a coefficient of determination of $r^2 = 0.00$ for density with both resistance drilling and sclerometer testing (larch (*Larix decidua*) and chestnut (*Castanea sativa*), (n=13)).

Additionally, the OLS model with the highest coefficients of determination obtained by Henriques *et al*. is compared to another OLS model also for a mix of pine species (n=50) by Morales *et al*. (2014) and found to differ significantly in intercept and slope illustrating how a relationship may be strong for one sample but inappropriate for another, from a different population. This is problematic for the development of a predictive model using this parameter.

One further study on historical roof trusses examined the strength of the relationship between the measures from resistance drilling and from sclerometer testing. For three separate timber elements the coefficient of determination, r^2, varied between 0.01 and 0.23 (Branco, Sousa and Tsakanika, 2017). Given that both measures are to be used to predict the same property of density, this shows great variability.

One review of resistance drilling collated coefficients of determination, r^2, for the relationship between resistance drilling measures and density and these are seen to vary from 0.09 to 0.90 (Feio and Machado, 2015). Additionally, Lechner *et al*. (2014) found a CoV of 55% for the values of resistance drilling while investigating a timber floor structure of large diameter (*Pinus sylvestris*) logs, despite previous studies reporting high CoVs, but never more than 37%.

The above mentioned studies concluded that the variation in resistance drilling measures can be controlled (to some degree) by better attention to the sharpness of the drill head, the direction and speed of drilling, accounting for both wood moisture content and the angle of the drill in relation to the growth rings in the timber element. Nevertheless, the high variability and wide range of coefficients of determination (relating resistance drilling and sclerometer testing with density) indicate that currently, it is not possible to use resistance drilling or sclerometer testing to confidently predict the mechanical and physical properties of in situ timber.

This conclusion is also reached by Kasal, Lear and Tannert (2010) who note that the determination of density using wholly non-destructive testing (resistance drilling, sclerometer and surface hardness testing) is not seen to lead to reliably accurate estimations. For this reason, they recommend that where possible other means are used when density is an important parameter to be found.

6.2.2.8 Screw withdrawal

This is an inexpensive technique that measures the force required to remove a screw inserted into a timber element, thus providing information that is used to predict local shear strength and density. The localised nature of this method reduces its usefulness for assessing large timber elements but is helpful in assessing the surface damage of timber elements (Ross and Pellerin, 1994). Unfortunately, the withdrawal of a screw from the face of timber element adversely affects its visual appearance. Additionally, any screws located at or near a knot provide large withdrawal resistances and so ideally knots should be visible on the surface of wood to be tested and, in any case, multiple measurements should be taken to reduce the impact of outliers (Kloiber *et al.*, 2015).

The screw withdrawal method measures shear strength which in turn is related to density. The relationship between normalized screw withdrawal resistance and density has been found to have a coefficient of determination of $r^2 = 0.92$ by Kloiber *et al*. (2015), which is stronger than the typical relationship between global density and density obtained from a block of clear wood cut from a structural sized test piece.

The strength of the relationship found by Kloiber is surprisingly strong, as one accepted and published correlation coefficient for the relationship between shear strength and density is only 0.6 (Joint Committee on Structural Safety, 2000), giving a coefficient of determination of $r^2 = 0.36$. So, caution must be applied to small scale studies until larger scale ones can verify their output.

6.2.2.9 Other methods

Digital radioscopy uses X-rays in a safe and controlled way, to penetrate solid timber elements and gain information on hidden construction details and internal conditions. As materials of differing densities absorb the X-rays differentially, it is possible to locate buried ironware (nails and screws, etc.) within a section of timber and to locate voids (possibly due to fungal attack) which are not identifiable from the surface of the timber. This technique requires access to two sides of an in situ timber element but could potentially avoid the need for (i) the removal of expensive finishes such as ornate plasterwork and, (ii) the need to carry out more destructive tests (Riggio *et al.*, 2014).

Digital radioscopy can also be used to determine density in situ but is not commonly used due to safety issues and a lack of experienced operators and equipment (Piazza and Riggio, 2008). In any case, for old timber elements (which may contain fissures and have irregular cross sectional dimensions), there may not be one definitive density measurement.

Therefore, this technique is typically limited to the depiction of the internal structure of a timber element. Its disadvantages relate to: (i) cost, safety and the need for specialist operatives, (ii) the 2D representation of the 3D interior of a timber element (in most common applications) and (iii) the difficulties of identifying and quantifying strength reducing characteristics (CEN, 2019b). Similar comments apply regarding similar techniques (gamma rays, nuclear magnetic resonance, etc.).

Ground penetrating radar measures the radiation of electromagnetic waves and its velocity and attenuation can be interpreted to identify physical or geometrical information about the subject of the investigation. The technique has been used with some success to identify hidden defects within timber elements, in particular the presence of excessive moisture. This technique is not widely used and its results are indistinct, requiring specialist post-processing and interpretation (Riggio *et al.*, 2014). Additionally, it is sensitive to the variation of moisture content and density and so requires calibration. Finally, the resolution of the technique is dependent on the relative size of anomalies in the timber element under investigation and the wavelength generated. Sometimes, resolution can be so low that detection is almost impossible (Tannert, Kasal and Anthony, 2010).

There are many other ways to measure different properties of timber that could relate to its mechanical and physical properties. For instance, infrared spectroscopy has successfully been used in a laboratory setting to assess the species of test pieces and estimate mechanical and physical properties. Although, initial results appear positive, there is much work to be done to bring this to the real world, involving the design and construction of new equipment, standardization of protocols, and the creation of databases of reference values (Sandak, Sandak and Riggio, 2015). This to do list summarises many of the issues facing the development and widespread use of NDT techniques for in situ timber.

6.2.3 Combining visual assessment, NDT and SDT

Following a desk survey, preliminary visual survey, measured survey and structural analysis, it is necessary to predict the mechanical and physical properties of the timber elements of an existing structure. Two overall approaches can be considered in the way that visual assessment, NDT and SDT are combined. One approach is to visually grade each timber element and allot it to a strength class and then, if necessary, use NDT or SDT to confirm or support or enhance the characteristic mechanical and physical properties on an ad hoc basis. This approach is commonly adopted; for instance in the 2019 SHATIS conference, 11 conference papers described this approach (SHATIS, 2019) and is also followed in many published research studies (Ross, 2002; ; Kasal and Tannert, 2010; Macchioni *et al.*, 2012; Feio and Machado, 2015; Ericsson *et al.*, 2017; Yeomans, 2019).

For 'new' timber, it is more common to combine visual, NDT or SDT parameters into a single predictive model to estimate the required mechanical and physical properties of structural timber (Hanhijarvi, Ranta-Maunus and Turk, 2005; Vega *et al.*, 2012; Ravenshorst, 2015). This is typically related to its grading for commercial reasons (sale for structural purposes) and so, generally also leads to the categorization of 'new' timber into strength classes.

A second approach for in situ timber would be to avoid the visual grading of in situ timber elements into grading categories, and instead to make use of visual grading parameters and include them with NDT or SDT parameters in a combined predictive model. This model could then be used for the assessment of in situ timber. In short, the first approach uses NDT/SDT to confirm or adjust visual strength grading and the second approach uses NDT/SDT to directly estimate properties.

A combined predictive model would need to be created before any assessment of an existing structure takes place. The creation of this predictive model is the main part of this thesis. Several studies have created interpretive models from NDT/SDT measurements for individual species to find the coefficients of determination between the model and the mechanical and physical properties of timber elements tested to destruction in the laboratory. Table 6.7 summarises five studies.

Table 6.7. Five studies with models and coefficients of determination, r^2, for static MoE and MoR with NDT/SDT methods, adapted from Feio and Machado (2015). Shaded cells are of particular interest (blue for MoE and green for MoR).

Study	Sample number	Species	New or old test pieces	Ultrasound stress wave velocity	Acoustic stress wave velocity	Penetration resistance	Knot /defect measure	Slope of grain	Drill resistance	Acoustic resonance	Density	MoE_{dyn} ultrasonic	MoE_{dyn} resonance	MoE local	MoE global	MoR
A	13	a	Old		✓	✓								0.63	0.71	
A	13	a	Old		✓	✓	✓							0.71	0.68	
A	13	a	Old		✓	✓		✓						0.69	0.74	
A	13	a	Old		✓	✓	✓	✓						0.83	0.76	
B	12	b	Old				✓		✓					0.62		
C	24	b, c, d	Old				✓		✓					0.06		
D	374	d	New							✓	✓				0.74	
D	374	d	New									✓			0.72	
D	374	d	New	✓							✓				0.74	
D	374	d	New				✓						✓			0.33
D	374	d	New				✓					✓				0.27
E	65	e	New				✓					✓				0.50

A (Cavalli and Togni, 2013); B (Branco, Piazza and Cruz, 2010); C (Piazza and Riggio, 2008); D (Vega *et al.*, 2012); E (Machado and Palma, 2011)

a (silver fir; *Abies alba*); b (spruce; *Picea abies*); c (larch: *Larix decidua*); d (chestnut; *Castanea sativa*); e (maritime pine; *Pinus pinaster*)

In Table 6.7, the strongest relationships with the two key mechanical properties are associated with the combined variables presented (and shaded in blue for MoE and green for MoR). For the smallest sample for MoE global, the combination of acoustic stress wave velocity, penetration resistance, knot /defect measure and slope of grain has a coefficient of determination of 0.76. For the larger sample, density combined with ultrasound or acoustic resonance has a coefficient of determination of 0.74. For MoR, the combination of knot /defect measure and MoE_{dyn} ultrasonic has a coefficient of determination of 0.50.

The sample size numbers in Table 6.7 and the age of the timber used in the studies typifies many other similar studies. The difficulties of obtaining large sample sizes of old timber naturally leads to many studies having sample sizes that are statistically too small to allow significant results to be determined. This is a weakness of all but one of the studies. For three of the five studies, numbers ranged from 12 to 24 test pieces; the remaining two studies used 65 and 374 test pieces each.

Cavalli and Togni (2013) report five further studies with sample sizes ranging from 3 to 99 and using the same species plus Southern pine. In this group of studies, the coefficient of determination of local static MoE with dynamic MoE (using flexural and stress wave methods) varies from 0.15 to 0.91.

As coefficients of determination vary from one study to another, it is useful to consider more studies which have combined slightly different variables. Table 6.8 combines the results of six studies comparing the predictive power of variables measured in a laboratory (Glos, 1995b; Hanhijarvi, Ranta-Maunus and Turk, 2005) to estimate MoR. The best single predictor is MoE and this can be slightly improved by combining it with knots. On their own or combined, knots, ring width and density are poor predictors of the bending strength of timber, despite these parameters being the basis of the visual grading of timber.

The benefit of combining grading parameters has been investigated and understood for decades (Glos, 1995b) and Table 6.8 and Table 6.9 show how the predictive powers of single variables increase in combination with others. In Table 6.8, for five of the six studies presented, the combination of MoE with knots has the strongest correlation with MoR and these results are shown in the green cells. In the sixth study (Study F), this strength of correlation is matched by that of knots and annual ring width with MoR (these cells are also shown in green).

Table 6.8. Coefficients of determination, r^2, of variables with MoR from six studies and extracted from Hanhijarvi *et al*. (2005) and Glos (1995b). Green shaded cells indicate the strongest correlations.

	With MoR, coefficient of determination, r^2						
	A	B	C	D	E	F	Unweighted average
Knots	0.27	0.20	0.16	0.25	0.26	0.25	0.23
Annual ring width	0.21	0.27	0.20	0.44	0.29	0.04	0.24
Density	0.16	0.30	0.16	0.40	0.34	0.16	0.25
MoE, edgewise	0.72	0.53	0.55	0.56	0.64	0.25	0.54
Knots + annual ring width	0.37	0.42	0.39		0.42	0.49 – 0.64	0.43
Knots + density	0.38		0.38		0.48	0.25	0.37
MoE + knots	0.73	0.58	0.64		0.68	0.49 – 0.64	0.64

A (Johansson, Brundin and Gruber, 1992); B (Hoffmeyer, 1984); C (Hoffmeyer, 1990); D (Lackner and Foslie, 1988); E (Fonselius, Lindgren and Makkonen, 1997); F (Glos, 1995b).

The explanation for the variation in the coefficients of determination (seen in Table 6.8 and Table 6.9) is likely to relate to several factors: test pieces being sourced from different species, trees of differing ages, from differing geographical locations, in differing sites with different growing conditions, subject to differing forestry management. The specimens may have been cut in different sizes and in different cutting patterns from different parts of the tree (i.e. juvenile and mature wood). Additionally, the experimental work may have been carried out in ways that differ and with varying sample sizes. What is remarkable is the similarity of the results bearing in mind all of these factors.

The third and final table showing the advantages of combining variables to strengthen relationships with the three key mechanical and physical properties is extracted from the Combigrade Project, initiated to improve the strength grading of new timber. In machine grading, MoE_{dyn} is commonly calculated based on natural frequency, which tends to give better correlations than time of flight. Additionally, MoE_{dyn} can either be based on a notional density (tabulated for different species) or a measured density of the timber under test. Both of these methods are used in practice, but as is clear in Table 6.9, using the measured density gives stronger correlations and so, even though it may not always be the preferred choice in machine grading, it is likely to be more useful to include it in a predictive model.

Table 6.9. Coefficients of determination, r^2, for spruce (n=111) and pine (n=108) structural sized test pieces with mechanical and physical properties from combining NDT variables. Adapted from Hanhijarvi *et al*. (2005). Shaded cells are of particular interest (blue for MoE and green for MoR).

MoE_{dyn} with notional density	MoE_{dyn} with measured density	Knot area ratio	Ring width	Global density	Visual grade (INSTA142)	MoR spruce	MoE global spruce	Density spruce	MoR pine	MoE global pine	Density pine
✓						0.46	0.67	0.19	0.62	0.79	0.50
✓		✓				0.51	0.71	0.24	0.73	0.79	0.55
✓			✓			0.52	0.75	0.36	0.62	0.79	0.54
	✓					0.60	0.89	0.62	0.69	0.92	0.81
	✓	✓				0.65	0.90	0.65	0.77	0.92	0.81
	✓		✓			0.60	0.90	0.62	0.69	0.92	0.81
	✓			✓		0.60	0.90	0.94	0.70	0.92	0.94
	✓				✓	0.64	0.89	0.65	0.77	0.92	0.81
		✓				0.21	0.11	0.03	0.54	0.34	0.35
		✓	✓			0.52	0.58	0.38	0.60	0.50	0.49
		✓		✓		0.55	0.65	0.94	0.70	0.76	0.94
		✓	✓	✓		0.60	0.73	0.94	0.70	0.77	0.94
			✓			0.38	0.53	0.35	0.34	0.40	0.38
			✓	✓		0.46	0.69	0.94	0.58	0.77	0.94
			✓	✓	✓	0.59	0.74	0.94	0.72	0.81	0.94
				✓		0.37	0.59	0.94	0.55	0.75	0.93
					✓	0.22	0.12	0.02	0.55	0.43	0.32

Two of the three combinations with the strongest correlations with MoR, shown by the green shaded cells, include MoE_{dyn} with measured density, indicating its likely inclusion in any predictive model. The combination with the third strongest correlation with MoR includes knot measure, ring width and density, indicating that there may be scope to create other (possibly weaker) predictive models which do not contain MoE_{dyn}. All of the combinations with the strongest correlations with MoE global, shown by the blue shaded cells, include MoE_{dyn} with measured density. Other combinations such as knot measure, ring width and density have weaker (but still strong) correlations with MoE which may be just strong enough to create useful predictive models which do not contain MoE_{dyn}. The laboratory measured density has a very strong relationship with global density and no further combining of variables improves this.

It must be borne in mind that the table above and the comments below apply to the commonly used softwood species in Europe and that for instance the helpful correlation between density and stiffness here may differ from that of species from, say, North America. This need to view the inputs of the predictive model building from a global perspective is important and applies to almost all of the relationships between variables in this thesis.

The combining of knot measure and ring width gives moderate coefficients of determination with both MoR and MoE. Whereas the relationship between visual grade and MoR and MoE are very weak to moderate. As visual grades are based on knot measure and ring width, this gives an indication of the deadening effect of banding into visual grades.

Two further interesting points arise from the study. Firstly, the stronger relationships evident with the pine timber (compared to the spruce timber) are thought to arise due to larger variability of knot sizes and density and corresponding larger variability of strength (Hanhijarvi, Ranta-Maunus and Turk, 2005). If formulating a predictive model that was species independent, the variability of one species compared to others will affect the model both positively and negatively. Greater predictive power will reduce the size of residual error in the model but greater variability in mechanical and physical properties will increase the breadth of confidence bands around lines of regression (however, as these are not large, the benefits outweigh the drawbacks). Secondly, the stronger relationships evident between global density and MoE compared to global density and MoR illustrate the global nature of stiffness, compared to the local nature of bending strength.

The above testing was extended to larger sample sizes (spruce n=1000 and pine n=1000), however, the results of the further testing by Hanhijarvi *et al*. (2008), while useful for grading purposes, did not significantly extend the results of the first set of testing. Finally, an interesting conclusion of the Gradewood Project was that, interpretive models, based on several measurements and which had a strong correlation with bending strength, remained relatively constant when applied to data from different growth areas (Ranta-Maunus, Denzler and Stapel, 2011). Whereas those models based solely on frequency measurement suffered from high variability, even within the same country. So, the stabilising effect of using several variables in the construction of a predictive model will act as a balance to the usual approach of modelling with the fewest parameters possible to obtain adequate predictive powers (Akaike, 1973), as more parameters may lead to greater stability for samples from different growth areas, different species, etc.

6.2.3.1 Species independent strength grading

Little was found in the literature on species free assessment of timber and so, just two studies are presented showing its feasibility. Assessing the in situ crushing strength and MoE of mine props is problematic due to a mine's requirements for low cost and low quality wood, commonly leading to the use of low density, low strength woods from a mix of species. In one study of 329 test pieces (previously used as mine props), 26 species were identified including both softwood and hardwood. Pilodyn® and time of flight stress wave measurements were used to successfully create models to supplement or replace visual grading (Chudnoff, Eslyn and Mckeever, 1984). The species independent models in this case were based on OLS regression and function usefully.

Another sector of the timber industry where species independent strength grading has been subject to research is tropical hardwoods. The wide range of tropical hardwood species and the high cost of destructive testing make any approach to strength grading with reduced destructive testing attractive. In any case the use of visual grading parameters on hardwoods is of limited use due to the typical absence of knots in straight grained timber. NDT combined with limited destructive testing has been used to develop a species independent strength grading model for hardwood timber with some success (Ravenshorst and Van De Kuilen, 2006).

The predictive model is based on density, knots and slope of grain, and uses machine measurements of density and MoE_{dyn} to quantify these parameters. The model relies on strength reducing equations accounting for knots and slope of grain, derived from structural mechanics (Ravenshorst, 2015).

Based on a testing programme on 30 different species (n=1500), two models were successfully developed to predict MoR and MoE. MoE_{dyn} and density have been used to predict MoR with a correlation coefficient of r = 0.82 and MoE_{dyn} alone predicts MoE with a correlation coefficient of r = 0.85. The novel method for strength classification uses NDT to replace a proportion of the laboratory testing required in strength grading. Only 25% of test pieces normally tested to destruction are treated this way and the remaining 75% of test pieces are tested using NDT. Weighted averages are used to determine 5 percentile values.

The model requires limited destructive testing of a sample of timber elements to establish: mean MoR, CoV of MoR, mean MoE and mean density for each species and growth area (van de Kuilen *et al.*, 2007) (it is noted that these statistics are not directly related to the Eurocodes). This approach still requires extensive laboratory testing to destruction which could cause issues with heritage structures which have no expendable structural elements. Any attempt to build up a bank of mean values and of CoVs would prove to be an enormous task, considering the breadth of the population of structural timber used in the UK over the previous three centuries.

Nevertheless, species independent appraisal of timber is seen to have its benefits and if a method could be developed without the need for extensive prior testing, then this has the potential of being adequately accurate and useful.

6.2.4 Research studies of old timber

The suggestion made to standardize and improve the testing and reporting of research into new timber (Ridley-Ellis, Stapel and Baño, 2016), applies to an even greater degree to in situ and historical timber. The use of systematic reviews or meta-analyses in medicine is well documented (Juni, Altman and Egger, 2001) and well used. It forms one of the foundations for evidence based medicine (Greenhalgh, 2014) and relies on good quality clinical trials and medical research that can be aggregated and sorted to help to cope with the vast number of research papers published. For research into in situ timber, a systematic review can assess the consistency of research outcomes across different populations, considering the significance of results in relation to the size of individual samples.

Even in medicine, where people's health directly depends on the quality of research and meta-analyses carried out, it is found that the standards of research work can be improved (Liberati *et al.*, 2009). In research into in-situ timber, there is a great need for standardization of reporting of individual pieces of research in order to allow their use in systematic reviews and meta-analyses.

In medicine, the Cochrane Collaboration comprises an international network of individuals and institutions carrying out reviews, often on a voluntary basis, using a standardized approach. The success of this institution is dependent on the standardization of controlled trials and methodologies for reviewing them (Grimshaw, 2004). The large volumes of disparate research papers produced regarding the assessment of in situ timber would similarly benefit from a standardized approach, allowing future systematic review – both qualitative and quantitative.

Combining NDT with visual strength assessment has been researched in the past, however, in addition to its non-standardised and dissimilar methodologies, this research generally suffers from small sample sizes and limited testing. A typical journal paper, for example, one by Cavalli and Togni (2013) presents research on just 13 timber beams of a single species of wood, Silver Fir (*Abies alba* Mill.). In this instance, visual strength grading in accordance with the Italian standard (UNI, 2004) was carried out together with a variety of non-destructive tests. In earlier sections of this chapter, a number of literature reviews are presented, which together, show the range of sample sizes and species of wood in journal papers. The small scale of most of the research presented is typical of the majority of research in this area and prevents the drawing of conclusions that can be considered as conclusive.

The latest version of EN384 (CEN, 2018b, p. 8) allows the use of historical test data from before 1995, using different test methods and at different moisture contents provided that '…*sufficient information exists to adjust the results to the reference conditions given in 5.3*.' How likely it is that historical test data will be available and suitable is unknown, however, this offers a potential route for some additional data to be used in assessing in situ timber. For this to take place, an agreed, published and administered protocol for the carrying out and reporting of tests on historical timber must be put in place. This is beyond the scope of this study.

Finally, small sample size issues with research into ‘new’ timber is certainly not always the case, as is illustrated by recent research studies (Conde Garcia, Fernandez-Golfin Seco and Hermoso Prieto, 2007; Hanhijarvi and Ranta-Maunus, 2008; Ranta-Maunus, Denzler and Stapel, 2011) making use of thousands of test pieces. However, for ‘old’ or historical timber, this is very much still the case.

6.3 Conclusions

A wide range of NDT and SDT have been reviewed and show a range of strengths of correlations with MoE, MoR and density. The strength of correlations can be increased, to be moderate or strong, by combining results from more than one test.

The single parameter with the best correlation with MoE and MoR is MoE_{dyn} which in turn can be calculated from stress wave testing. Ultrasonic and acoustic time of flight and acoustic resonance all are seen to provide a good basis for the calculation of MoE_{dyn} ; MoE_{dyn} calculated from stress wave testing and incorporating density is better than using a notional density in the calculations.

Two approaches vie for the best correlation with density (i.e. the density of a cut section from a structural sized element, in accordance with EN408): (i) the averaged density from more than one small specimen cored or cut from the element and tested in a laboratory and (ii) DCE. These parameters are the most appropriate for the global density (i.e. the density of the entire beam calculated from its mass) of an element also.

Although resistance drilling, sclerometer testing, modified hardness testing and screw withdrawal testing all show a range of correlations with density, their relationships are weaker than the above two methods and show greater variability. Also, the impression from research papers is that the efficacy of these methods is heavily dependent on the skill and experience of the operator. This is not good for a predictive model for general use and so their use is not considered further.

Several studies have shown that combining predictor variables can increase coefficients of determination with MoE and MoR. The most promising variables to combine with MoE_{dyn} are knot measure, rate of growth, slope of grain and density. The review of previous studies did not suggest that the two proposed methods of estimating density can be improved through combination with other techniques.

There is a theoretical justification for combining MoE_{dyn} with knot measure for the prediction of MoR as, those characteristics which may affect the bending strength of a timber element may be too small to be detected by stress wave testing, but would be included with say, a knot measure. Additionally, a predictive model with more variables is expected to be more robust to variability (across growth areas and species) than one with fewer.

It is a shame that research in so many studies of 'old' timber is carried out in such a variety of ways and restricted to small sample sizes. These shortcomings can to some degree be overcome, in general, by standardising research into 'old' timber and, in particular, by complementing this by using appropriately large samples of 'new' timber in creating the predictive models for 'old' timber.

One final point to note is that in all the studies reviewed, no transformation of variables has been used. This suggests that, in the creation of predictive models, no transformation will be needed, however this should be checked in any case.

The next chapter takes a wider view of testing and model building to review the contexts within which predictive models must be developed.

Chapter 7 Factors affecting the models

7.1 Introduction

Chapter 8 focusses on the statistical development of the predictive models. Their development must be seen in context and so in this chapter a step back is taken, away from the data, to discuss the broader factors affecting the creation and application of the predictive models.

This chapter discusses the observational nature of this study and the differences between the population of in situ structural timber elements in the UK and the sample that it is based upon (and for that matter all future samples for future studies too). How the numbers of samples and sample sizes affect distribution and regression models differently is also discussed.

Next, follows consideration of the quality of in situ timber in relation to when and why a structure was originally built and the quality of information gained during the appraisal of a structure. Service life and mechanical damage is considered. Then prior grading in relation to the predictive models and particularly in relation to how they may be used is evaluated. Finally, some suggestions are given to account for all of the above.

The unique contribution to knowledge described in this chapter is the consideration and accounting for of significant factors which affect the new predictive models:

(i) selection bias
(ii) potential prior grading
(iii) the deterioration of wood during its life in service.

7.2 Population and sample

7.2.1 Vast population and inadequate sample

In visual grading of new timber, a stratified and weighted sample is taken that is intended to be representative of a given population; the physical and mechanical properties of the sample are considered to be representative of the characteristic values of physical and mechanical properties of the population, based on: given species, given growth areas, given forestry and saw milling practices etc. Characteristic values derived from the sample are then used in design. The key aim is to create a sample that is genuinely representative of the population accounting for known and unknown variables.

The population of in situ structural softwood timber elements in the UK is vast, spanning several centuries of growth periods and forestry practices. It includes growth areas and species from around the world. It is not possible to create a sample (or series of samples) that adequately represents this population. This is mainly due to the size of the population, and its drawing on past resources of timber (which cannot be replicated in the present) and these issues are compounded by (i) the variety of service life conditions that the timber elements have been subject to, (ii) visible or hidden mechanical damage that has occurred and (iii) possible prior grading.

Nevertheless, this issue can be improved by significantly increasing the size and breadth of samples tested for the predictive models. Due to the size of this task, this is unlikely to be achieved by an individual testing institute. It can be tackled by pooling research results from many research institutions over time. The current disorganised approach of testing and reporting on samples of old timber elements from existing structures is inadequate to address this challenge. It is important that the data within the expanding data set is adequately consistent in its creation (controlling for moisture content, humidity and temperature, size and duration of tests, etc) and adequately detailed (date of construction of in situ timber, type of structure, geographical location, species, etc.). Similar to Cochrane, a philosophy and systematic protocol must be agreed on for the composition of the expanding data set: what data must be included and how.

In the meantime, the predictive models in this study make use of results from the testing of ‘new’ timber. Therefore some consideration must be given to adjusting these models. This leads to the question of how a predictive model based on new timber differs from one based on both old and new timber. To answer this the relationships and differences between the predictor variables and the key mechanical and physical properties must be understood for both old and new timber.

7.2.2 Data set used in this study

In the creation of predictive models for existing timber, it is not practicably possible to create a representative sample of the vast population of in situ structural timber in the UK. In place of a truly representative sample is a limited sample of convenience. The data set in this study is from four minor species grown in the UK and so is significantly different to the population of in situ structural timber in the UK. For instance, in the data set, the properties of wood from the UK growth area differ from wood from the continent of Europe, being typically less stiff and dense; and all trees in the study (i) are relatively young and so have a greater proportion of juvenile wood compared to mature wood and (ii) are from managed forests which differs from timber felled from first growth forests, used in much of the older building stock in the UK. Thus, the initial data set can only be considered to be a pilot study or a starting point for a predictive model, which would need to be built upon an expanding data set and recalculated afresh as the data set is increased in the future.

The predictive model is based on the relationships between the results of NDT and visual testing of the limited sample and is applied to the population. This assumes that the relationships between (i) the results of NDT and visual testing and (ii) the values of physical and mechanical properties of an individual structural timber element remain similar regardless of species, growth areas, forestry and saw milling practices, year of construction, etc. This assumption needs confirming.

It is noted that the relationship of MoE_{dyn} with MoE and MoR is commonly used in the mechanical grading of timber and that this relationship for new wood is influenced by a wide range of known and unknown factors: visual features, microscopic features, chemical composition, genetics, nature of soil, microclimate, forest management. This study effectively proposes to extend this long list to include some additional factors relating to in situ timber, which is a reasonable proposal, that nevertheless should be investigated and confirmed in the future.

Reference to Chapter 8 demonstrates how the relationships between MoE_{dyn} and MoR 0.05 quantiles vary by species and the species specific regression models have similar but different slopes and intercepts. So, considering only species, the general model (i.e. the model based on the whole data set of all four of the minor species) will also vary from the species specific models. As more data is added to the model data set in the future, including more species, the degree of difference between species specific models and the general model will change and need to be reviewed. The differences in the models due to different species is expected to be compounded by the variations due to growth areas, forestry and saw milling practices, the year of construction, etc. This is discussed further below.

7.2.3 Selection bias

When a sample is not representative of a population due to the selection procedure, such as the sample in this study, its characteristics may differ from the population in significant ways, this is termed selection bias. Selection bias is important as the internal and external validity of models based upon biased data are undermined, i.e. the coefficients of regression of models may be incorrect and a model based on a biased sample may not be applicable to its population. There are several types of selection bias that should be considered:

Sampling bias is due to the way a sample is collected which leads to a biased sample in which all groups of an intended population are not equally likely to be represented.

Studies bias occurs due to a biased choice of publications included in a literature review or meta-analysis. In this study, the initial review of literature focussed on structural engineering texts which represent some of the ill-informed views of structural engineering practitioners. Unfortunately, some of these views, such as (i) treating knots as voids to explain changes in bending strength and (ii) recommending the use of visual grading codes to assess individual in situ timber elements (CEN, 2019b), are not widely contradicted in academic literature for a number of reasons (Spiegelhalter, 2019). However, the final extended review of literature and the experimental work in this thesis, has allowed the initial studies bias to be addressed

Time interval bias and attrition bias arise in longitudinal studies and so do not relate directly to the time-related selection biases that affect this study. Firstly, the data set on which the predictive models of this study are based contain solely new timber and needs to be expanded to include timber from each century of the current building stock of the UK to better represent this population and its variability. Secondly, the 'snapshot' nature of sampling used in almost all studies, fails to represent the greater variability in the properties of timber which occurs over modestly longer timescales such as a several years, let alone several decades (Ridley-Ellis and Cramer, 2020). This variability is of particular importance for predictive models for salvaged population design.

To more fully understand the implications of the sampling method used in this study, it is important firstly, to understand the differences between observational data and experimental data and secondly, be aware of the interrelated ways that independent variables affect the dependent variables. For assessing a material's structural properties (e.g. steel or concrete), the Eurocodes broadly attempt to adopt the experimental approach, as material samples are taken which are intended to represent the entire material population.

The gold standard of the experimental approach is the double blind controlled experimental trial, commonly used in medical science to investigate causal relationships between interventions and their effects. Whereas, in economics and the social sciences, observational data is commonly used, as this is all that is available and this can be adequate to investigate correlations between factors but is not sufficient to investigate causal relationships. The limited data available for this study is similar to observational data, but unfortunately is not especially rich nor complete, as so many factors are simply unknown or unknowable.

Considering the interrelated ways that independent variables affect the dependent variables, there is a difference between (i) the models for MoE and density and (ii) the model for MoR, due to the nature of the measurements taken and the strength of their relationships with the properties under investigation. The key predictor of MoE is MoE_{dyn} and it has been shown that these two properties are both influenced in similar ways by the same factors. A good predictor of the density of a small block of wood cut from a joist is the density of a pair of small diameter cores of wood from the same joist. There is a strong correlation for density because the two measurements are both of the clear wood in the same joist but are carried out in slightly different ways (which adds to the variability already present in the joist). In short, there are strong relationships between MoE and density and the key data used in their predictions (MoE_{dyn} and density of small diameter cores). The predictive strength of MoE_{dyn} for MoE can also be strengthened by combining with other factors such as knot measure or density.

Key factors that affect MoR include species, genetics, soil, climate, forestry and sawmilling practices. Unfortunately, for in situ timber, these are unlikely to be known nor even knowable. Also, as no single factor is strongly correlated with MoR, the best predictions are made by combining measurable factors such as MoE_{dyn} and knot measure, or density and knot measure. However, changes to the key factors affecting MoR (such as species and forestry practices) affect the measurable factors in varying degrees.

This is problematic for both mechanical grading of new timber and for assessing the properties of in situ structural timber. For new timber, this is illustrated by the findings of the Gradewood Project regarding machine settings. Now, the settings of grading machines are based on measurements of indicating properties such as resonant frequency, density and knot measures. The Gradewood Project made use of an extended data set and found that for the strength of Norway spruce, the grading settings from (i) central Europe and (ii) Northern Europe could be the same, despite the size of the geographical area contained therein. However, for Scots pine, separate grading settings would be required for (i) Germany, (ii) France, (iii) UK and (iv) Nordic countries (Ranta-Maunus, 2009). So, growth area, affects one species in a different way to another species in relation to changes to MoR and to changes to grading indicating properties.

The effect of factors from the original growing and processing of wood into structural timber are compounded by the effect of factors from the service life of the structural timber, which also are impossible to determine. From this, it is easy to understand why the coefficient of determination for the prediction of MoR is so much weaker than for MoE.

Thanks to the wide variety of factors which may have affected the structural timber in the UK's building stock over several centuries, there are many sub-populations which are defined by particular groupings of these factors. So, this study is an example of 'infinite regress' explained by Berk (1983) as a question as to how can a random sample represent a sub-population, which in turn must represent larger sub-populations up to an entire population.

Consider the possibility that the data set for the predictive model for MoR could be expanded enormously, through participation of many engineers and researchers over many years. One contributory data set may be a random sample of European spruce joists in a structure built in say 1880 in London, this is a non-random sample of European spruce joists used throughout England that year, which in any case would be a non-random sample of European spruce joists used throughout the 19th century, of all centuries, of differently sized joists, found in more or less prestigious structures. So, the question to be answered is not whether bias exists, it is whether the bias can be understood and accounted for (Berk, 1983).

Thus, come what may, it is necessary to detect and correct the selection bias in the predictive model for MoR. This bias cannot be detected solely by examining the model data set. The characteristics of the data set must be compared with those of the population. Commonly used statistical tests to do this include χ^2 and logistic regression analyses, however, once detected, neither of these tests can be used to correct bias (Fielding and Gilbert, 2012). Beginning around the late 1970s, sample selection models were developed in econometrics to both detect and correct for bias. One of the first models, by Heckman (1979) involves two steps and is still used today along with several variations and other models which have also been developed using similar approaches (i.e. comparing models based on (i) the sample and (ii) the population). For this study, the first step in Heckman's two step estimator is to create a *'substantive model'* based on the study data set (i.e. the 527 observations of the four minor species used in this study). The second step is to create a *'sample model'* which is based on a data set which represents the population of in situ timber in the UK. This second data set must take into account many varied factors (such as species, age, in service history, prestige of building, prior grading, growth area, forestry and sawmilling practices, etc.). The two models are combined to create the *'sample selection model'* which can be used to detect selection bias and to correct the substantive model for this (Cuddeback, Orme and Combs-Orme, 2004).

That "…*corrections for sample selection bias… must overcome many practical difficulties*…" (Berk, 1983, p. 396) is an understatement for this study because of the lack of knowledge of the population of in situ timber, which has been the subject of very few and almost always very small studies. In any case sample selection bias is not tackled consistently well across other disciplines, even where it has been used for several years (Cuddeback, Orme and Combs-Orme, 2004; Certo *et al.*, 2016; Tudball *et al.*, 2020) and when applied wrongly, it can be inaccurate and even worsen estimates.

Despite the difficulties, researchers must use this observational approach for old timber. This is a clear departure from the experimental approach used in grading new timber, where care is taken to create representative samples. So, the whole of the field of study of the assessment of old timber in existing structures (that is both to remain in situ and to be removed and reused) is subject to selection bias and so researchers should expand their knowledge and skills in detecting and correcting this (Cuddeback, Orme and Combs-Orme, 2004).

In attempting to correct for sample selection bias, it is important to have a general idea on the source and direction of bias before applying any sample selection model. For this study, even though full consideration is not possible due to a lack of data, consideration in general terms may be possible. For instance, if data for stronger or stiffer timber is systematically missing from a predictive model, then it may be possible to assess how model regression coefficients would be affected by the inclusion of the missing data. This is illustrated below.

The correlation of MoE_{dyn} with MoR (used in the predictive model) is strongly related to the correlation of MoE with MoR. Data for both MoE and MoR was gathered in the Gradewood Project (Ranta-Maunus, Denzler and Stapel, 2011) from several European countries, and mean values of MoE and MoR are available from the project and are plotted on the graph in Figure 7.1 along with data from the four minor species (upon which the predictive model of this study is based). It is seen that the timber from the UK is relatively less stiff than timber from the continent (as is typically the case) and the slope of the predictive model for MoR based on MoE will be expected to reduce as the model data set, which must include much timber from the continent, is expanded. It should be noted that only means are plotted in Figure 7.1 which appear to show the UK data points as outliers, however, when all observations of each data set are plotted, there is much overlapping of data points.

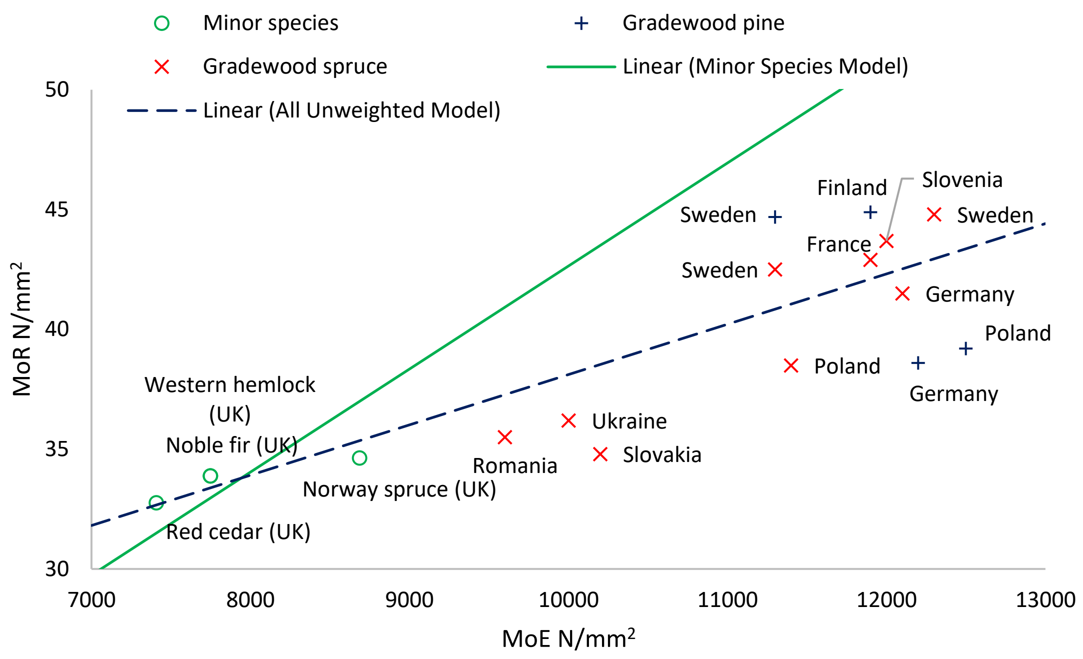

Figure 7.1. MoE vs MoR showing means from the Minor Species Study and the Gradewood Project

The two OLS regression lines are based on (i) the 527 data points of the minor species data set and (ii) the unweighted means of the same data set and those of the Gradewood Project. Towards the right hand side of the graph, for MoE = 13 000 N/mm^2, the estimates of the two regression lines differ by a factor of 0.8 and for lesser values of MoE, the factor grows closer to 1 around MoE = 8 000 N/mm^2. Data is not available for the 0.05 quantile of MoR, but if it is assumed that the differences between its estimates are similar to the differences between the estimates of mean MoR, then by extending the data upon which the model is based, the estimated values of the 0.05 quantile of MoR would be expected to reduce by a factor of around 0.8. This is simply a quick assessment to gauge the scale and direction of the changes to predicted values of MoR_{LCL} as the sample selection model is applied. It should be borne in mind that the strength of any ecological correlations, based on aggregated data, such as that in the graph, may be overstated when compared to individual correlations (Freedman, 2001). Thus, care must be taken in the future when aggregating data from sub-samples. Additionally, care must be taken to improve the consistency with which new data is obtained and reported to allow its easy assimilation into a larger dataset and this is a recommendation made in Chapter 9.

To gain a general idea of the population of timber from beyond Europe, an older collection of data is accessed (Lavers and Moore, 1983) which mostly covers timber from Canada (but also from New Zealand, Kenya and South America) and mean MoE and MoR values are plotted together in Figure 7.2. This data is from the testing of small clear specimens, but it is expected to show roughly similar trends to data from structural sized specimens. The line of OLS regression of mean MoR for the four minor species (which relates to structural sized testing and not small clears) is also plotted onto the graph and its slope and that of worldwide timber are similar. The shift upwards of the worldwide timber regression line is considered to relate to both the sizes of the test pieces as well as the nature of the wood.

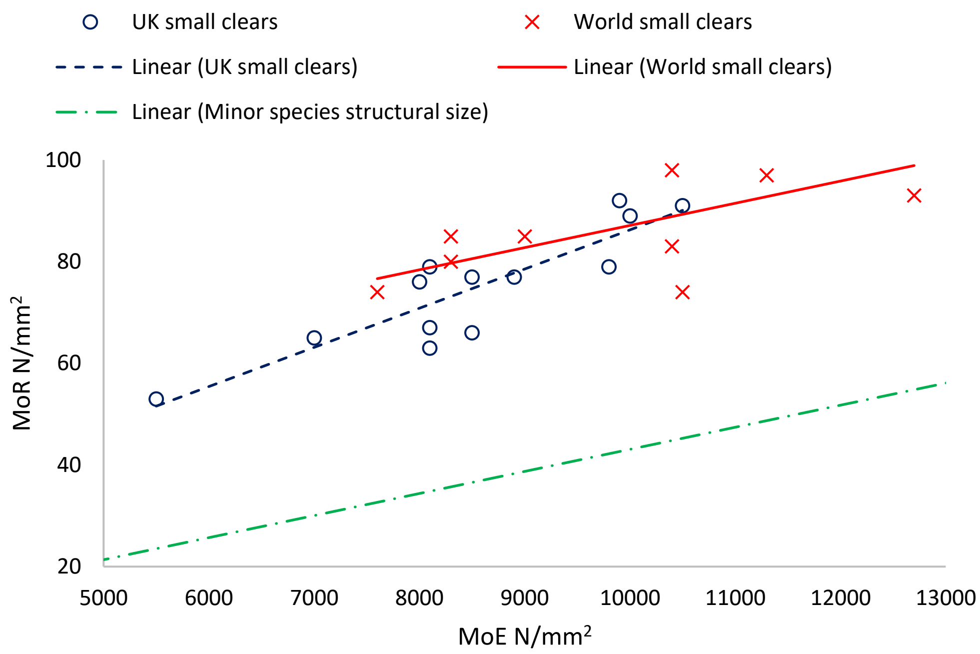

Figure 7.2. MoE vs MoR showing regression lines for means from the Strength Properties of Timber)and the regression line of the predictive model

Thus, a slightly mixed picture is appearing that will improve as more data is used in the samples of the models to help them to better reflect the population. It is noted that an all species model which must necessarily accommodate a variety of relationships between predictors and MoR will not be as efficient as a series of species specific models doing the same. So, even though the current approach is not ideal, it is at least feasible based on the very limited data held on the population of in situ structural timber. Whereas the species specific approach currently requires considerably more and better data.

The goal of creating a reliable predictive model is influenced by the need to make one that can be applied safely by structural engineers. So, despite economic and environmental pressures to make a model whose estimates of stiffness and strength are as high as they can be, one method to manage the model error due to sample bias would be to make use of a partial factor (see Section 8.5) which could be applied to estimates to ensure that they are low enough to be used safely in practice. This could be reviewed as the model data set expands and its selection bias reduces.

In summary, selection bias is considered to particularly affect the predictive model for MoR and should be controlled through the use of a sample selection model that will take time to create. In the meantime, a simple partial factor can be used which inevitably reduces the accuracy of the model but allows its use, even though based on a biased sample. The more direct relationships between predictors and estimates of MoE and density render their predictive models less impacted by selection bias.

7.3 Sample size and number of samples – different models

The Eurocode approach to visual grading and strength classification requires extensive testing of large samples which are representative of size limited growth areas and species. The methods described in this thesis are initially based on a modest sample size of just four minor species from the UK. Due to the variability of timber, it is necessary to consider the effects of sample size and number of samples used in the predictive models developed in this thesis, particularly in relation to the way that these are accounted for in the Eurocodes. In the Eurocodes, 50% two sided lower confidence limits are used in relation to sample size and a single factor k_n is used in relation to the number of sub-samples.

Sample size

For the mean of a model based on distribution statistics, the confidence interval relates to the spread of data points around the mean of the sample and is based on the standard deviation of the whole distribution. As the sample size increases (assuming that the standard deviation remains constant) the rate of decrease in the size of the confidence interval is approximately inversely proportional to the square root of the sample size. Reference should be made to Table 7.1 which shows the 50% confidence width around mean MoE decreasing as sample size increases: from 0.31 kN/mm^2 (n=100) to 0.13 kN/mm^2 (n=500). This is a decrease of 42% and an absolute decrease of 0.18 kN/mm^2. The various samples in Table 7.1 are based on randomly selected test pieces from the minor species data set and so, due to the variance in the timber, the upper and lower limits do not follow a smooth line.

A graph illustrating reducing confidence intervals is shown in Figure 7.3. The reduction of the interval widths for both distribution and OLS regression models can be seen as the sample size increases from 50 to 527.

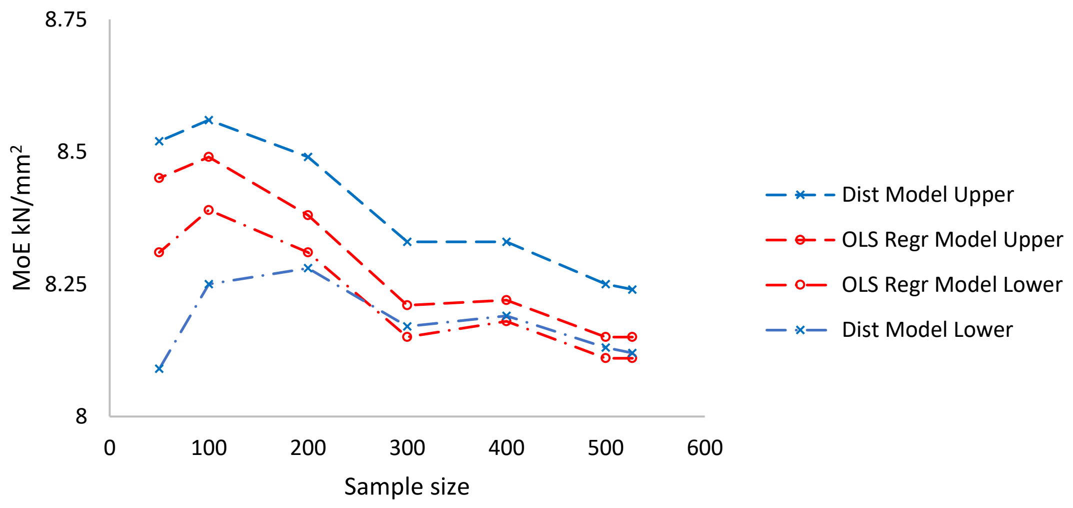

Figure 7.3. Graph showing confidence interval width and sample size

For an OLS regression model, the confidence interval, is based on its mean square error (MSE), which reduces slowly, as the MSE term in the calculation of the confidence limits is multiplied by both the inverse of the sample size (n) and a second term related to the spread of the predictor data points. As the MSE in the regression model is smaller than the standard deviation in the sample distribution model, confidence intervals are smaller, which is seen in the graph. Table 7.1 shows the confidence width decreasing as sample size increases from 0.10 kN/mm^2 (n=100) to 0.04 kN/mm^2 (n=500). This is a decrease of 42% and an absolute decrease of just 0.057 kN/mm^2. This relates to the reduction in overall width of the confidence interval which translates to the lower confidence limit changing by just half of this value and so, the change of MoE_{LCL} is just 0.029 kN/mm^2. So, for a fivefold increase in sample size, the absolute change for MoE_{LCL} is very small and is around three times smaller than for the distribution model. Nevertheless, in order to match with the Eurocodes, this approach is followed in the new predictive models for MoE, MoR and density.

Table 7.1. 50% confidence limits around the estimates of mean MoE for two models

Sample size	Distribution model				OLS regression model			
	Lower limit	Upper limit	CI width	Compare to n=100	Lower limit	Upper limit	CI width	Compare to n=100
(n=)	kN/mm^2			(%)	kN/mm^2			(%)
527	8.12	8.24	0.12	41	8.11	8.15	0.04	41
500	8.13	8.25	0.13	41	8.11	8.15	0.04	42
400	8.19	8.33	0.15	47	8.18	8.22	0.05	48
300	8.17	8.33	0.16	53	8.15	8.21	0.06	58
200	8.28	8.49	0.21	68	8.31	8.38	0.07	69
100	8.25	8.56	0.31	100	8.39	8.49	0.10	100
50	8.09	8.52	0.43	141	8.31	8.45	0.13	137

Number of samples

With regard to the number of samples used to create confidence limits, this is of importance to both models for different reasons. In visual strength grading timber from a new growth area, it is essential that the aspects that influence the properties of the timber are understood and correctly represented in samples used. This depends on an adequate sample (or series of sub-samples) being created and analysed. This process is repeated for new timber from other new growth areas. In each instance, fresh sampling is needed to characterise the new timber. However, due to the observational nature of the predictive models for in situ timber (which are based on all common species and all common growth areas), each new sample will cumulatively add to the original data set to improve the models and to reduce selection bias. Thus, the way that each new sample is used in each model, is quite different and the application of a penalty factor to account for number of sub-samples does not apply to the predictive models. Therefore, this is omitted and in its place a sample selection model is proposed.

7.4 Quality of existing structure

That different materials are required for different projects applies in the past as it does in the present. Thus, the quality of structural timber used varies according to the nature of a project, its prestige, its funding and the perceptions of the client and its designers.

The range in the quality of cast iron and steel found in a range of historical buildings and bridges is documented (Bates, 1984; Swailes, 1996; Bussell, 1997) and informs the values of permissible stresses adopted in design checks. Timber also is known to have been specified differently for different projects, requiring different species, growth areas and degrees of quality (House of Commons, 1835; Donaldson, 1860). So much so that the expected life span of a '*fourth rate house*' built from '*inferior Canadian timber'* was expected to be only a little more than half of that for one built from Memel timber and Christiana deals. Thus, it is not simply the case that all old buildings have stronger and stiffer timber than new ones. Judgement is needed regarding the quality of the structure in question.

In mid-19th century Britain, Nicholson (Nicholson and Tredgold, 1848, p. 57) instructs carpenters on the strengths and weaknesses of home grown (i.e. British) timber, Foreign European timber and timber from America.

> *"Of the Foreign European kinds, red or yellow Fir, in timber and deals, is brought from Norway, Russia, Prussia, and Sweden: the most esteemed kinds are from Riga, Memel and Dantzic. White fir, in deals, is brought from Norway, Sweden and Russia: the most esteemed are from Christiana…*
>
> *The red or yellow fir is that most usually employed in the construction of buildings, for girders, beams, joists, rafters, and almost all external carpenters' work: and in the state of deals, it is used for the greater part of the joiner's work…*
>
> *From America is imported Red and White Pine, White Deals, and Oak. The white pine is often a clear, uniform, and straight-grained wood, and is of an excellent quality for mouldings: but none of the American pines are durable, and when confined in close places, or built into walls, they are very subject to dry-rot…*

Of our home kinds of wood, Oak is the only kind that is generally useful in buildings, the wood of our planted firs being vastly inferior to that from the Baltic or Norway, and is not fit for any purposes where much strength or durability is expected."

Hence, any carpenter or architect, having read and believed Nicholson would specify timber in accordance with the above, i.e. prestigious buildings would require timber from Christiana and lower grade buildings, from America or, heaven forbid, from Britain.

Thus, alongside the carpenter's experience and intuition, and alongside availability at the wood yard, there is another influence of textbooks which in time are followed by codes of practice. Additionally, an architect or quantity surveyor or informed client may also have their own views on the appropriateness of certain species or growth areas which will shape any specification, bill of quantities or set of construction drawings.

Apart from the specification of species and growth area, the quality of the timber structural elements themselves are also described in specifications as for instance, the following terms are common in many 19th century specifications: 'best', 'crown', 'free of large knots, shakes and sapwood', 'sound', 'well-seasoned', etc. (Donaldson, 1860).

The use of these terms does not in itself ensure that the timber finally chosen to be used will be significantly better than the timber rejected for use in the buildings. These terms are based on appearance grading or visual inspection of timber elements and, as visual grading parameters such as knots and slope of grain are shown to have only a weak relationship with strength and stiffness, it is possible that this 'prior grading' will not have significantly affected the distribution of properties in the set of pieces of timber in a building. However, one purpose that these terms could usefully have served, is to remove the very worst joists (with large knots, steeply sloping grain, etc.) at least from the more prestigious projects, especially those meriting a clerk of works for the client. Conversely, the very worst joists removed from the more prestigious projects are more likely to finish up in other low quality structures.

Without contemporaneous records or an extensive survey of a structure, it is not possible to estimate with certainty the likely outcomes of the various influences presented above, even when the age and location of a structure is known along with the level of its original quality of construction. Nevertheless, with further detailed study, it should be possible to determine the most important influences (and their outcomes) by taking account of the era and location of construction, and the level of quality of the structure. Initially, this may be a broad brush model that could be refined, little by little, as historical studies are expanded.

Just as the sensitivity and specificity of medical diagnoses are improved with the inclusion of contextual information (about the patient, their lifestyle, past history, etc.) above and beyond the results of medical tests, similarly, the model estimates for in situ timber can be complemented by contextual information about the structure, its usage, its history, etc. Four key factors that influence the quality of materials used in a structure are given in Table 7.2.

Table 7.2. Quality of existing structure

High	Low
1. Importance of building (and associated likely size of construction budget)	
Prestigious or institutional property such as school, university, library, museum, stately home, hospital	Second rate or low quality building such as terraced housing in a mill town, single storey workshop and storage area in a factory or farm building or an alteration or later extension to an existing building
2. Location of structural element within the structure	
Primary location such as family living quarters in a stately home, boardroom or offices in a factory	Secondary or tertiary location such as an outhouse or work shed in a factory
3. Form of contract	
Built for a client's future use Known and reputable builder Known and reputable architect	'Spec built' for a developer to sell after construction Unknown builder Unknown architect
4. Era of construction (Richardson, 2000)	
	Time of war or austerity (when timber is in short supply) such as WWI, WWII and the 1950s Time of economic depression (when the cost of building materials is of greater importance) such as 1810s, 1860s, 1920s and 30s

7.5 Service life

The service life of in situ timber elements cannot be known for certain and its effects, due to, for instance, cyclical changes in moisture content or temporary overloading, are therefore rarely possible to find out with certainty from a desk study. Unfortunately, changes in the properties of in situ timber following an adverse service life cannot be detected visually, therefore NDT and SDT must be used.

Each of the three mechanical and physical properties are affected differently by an adverse service life:

1. Density could be reduced due to biological attack, and this could be picked up through NDT/SDT in situ. It is not always detectable without NDT/SDT.
2. Stiffness of timber elements could be reduced, and the expectation is that this would be picked up through lower MoE_{dyn} estimates made from NDT in situ.
3. Bending strength of timber elements could be reduced, and the hope is that this would also be reflected in reductions in MoE_{dyn}.

Thus, it is assumed that reductions in mechanical and physical properties are accounted for in reduced values of SDT and NDT results and that no further adjustments to the models are needed. This assumption needs further research to confirm or otherwise, particularly in the case of MoR.

7.6 Mechanical damage

Mechanical damage that has occurred during the service life of an in situ timber element should also include the effects of in situ testing (SDT) and planned subsequent, partial demolition, refurbishment and other works. This damage can be due to (i) holes and notches, (ii) nails, screws and fastenings, and (iii) other mechanical breakages. As such, it may be visible to the naked eye or detectable with NDT or SDT. Unfortunately, without more research, it is not possible to be sure that it will be detected by NDT or SDT or visual inspection.

Larger holes and notches are relatively straightforward to account for in the design calculations a structural engineer would carry out, based on measured reductions of cross sectional area and taking account of the types and directions of stresses calculated to be within the remaining section. Additionally, changes to the exposed surface of timber elements may change their fire resistance.

Small holes relating to old nails and other fastenings are far less straightforward to measure and account for. Due to their intermittent nature, these were not expected to significantly affect MoE, which relates strongly to the clear wood properties of structural timber (Kasal, Lear and Tannert, 2010). However, this damage is expected to potentially affect MoR, which is typically affected by intermittent points of weakness, and whose impact is amplified when occurring close to points of high bending stress. Reference should be made to Sub-section 2.5.5 for a discussion on the relationship between nails and strength and stiffness.

Based on anecdotal evidence (the author has observed the failure of reclaimed timber often occurring at the locations of nail or screw holes) and limited evidence from the literature (Nakajima and Murakami, 2007) this issue is one that must be accounted for in predictive models for both MoR and MoE. Currently, there is insufficient research into the effects of damage due to small fixings, and although this is currently being investigated by the InFutUReWood research project (Ridley-Ellis and Cramer, no date), more research is needed to assess the measurement and implications of damage due to small fixings.

Until adequate research is published, the predictive models are unable to accurately account for the effects of damage due to small fixings on MoE and MoR. A suggested interim approach would be to make use of safety factors which could vary according to the degree of damage found or expected to be found in any particular timber element (see Section 8.5). Elements could be classified according to their estimated extent of damage which in turn would be based on the type of structure and its date of construction, evidence of its past uses and maintenance, the location of elements within the structure and visual inspection and possibly NDT of the element in question. Visual inspection is by far the most important of these factors.

Additionally, mechanical breakages that have occurred to timber elements during their service life could be dealt with on an ad hoc basis following careful visual inspection and potentially limited load testing. However, this would be time consuming and expensive and unlikely to lead to definitive conclusions and so the most likely approach to this would be to replace (or strengthen) all timber elements that are observed to have suffered significant mechanical breakages. This is likely to be the cheapest and safest approach in most circumstances, although in high value structures with heritage value, the former approach may be more appropriate.

Finally, density is required to assess fire resistance and to design connections. Regarding embedded steel fixings and fire, the behaviour of timber and steel is complex, depending on the size and exposure of embedded steel elements and this behaviour is further complicated at connections by the ways in which stresses are transferred. The insertion of a nail or steel dowel into a softwood joist will increase its density and the steel will conduct heat more quickly into the joist which may increase its rate of deterioration in fire (Carling, 1989). The insertion and subsequent removal of the same fixing will leave density unaffected and will create a weakness in any potential protective outer charred layer of the joist; again affecting fire resistance. So, even if it could be determined accurately, on its own, the combined density of wood and embedded steel fixings is no guide as to how a joist's performance in fire will change; instead, a detailed visual inspection and engineering judgement is needed.

Similarly, regarding embedded steel fixings and connections, correctly estimating changes to density due to embedded fixings is little help in understanding the complex behaviour of a connection. Thus, rather than attempt to quantify an overall or local change in density due to nails etc. it would be prudent for an engineer to focus more closely on the locations of bearings and connections and to use a detailed visual inspection and engineering judgement.

7.7 Quality of desk study information

Some consideration must be given to the extent of information obtained on the contextual background, described in the previous sub-sections. Obtaining useful information on the past history of a building can be difficult and the outcome of desk studies, in terms of quality and volume of information, lies outside the control of an engineer, regardless of skill and application. Nevertheless, the better the desk study outcome, the better that the quality of the existing structure can be determined and hence the model outcomes improved. Table 7.3 describes the two key aspects of desk studies in this respect, regarding construction work and service life.

Table 7.3. Quality of desk study information

High	Low
1. Construction information: date of construction, form of contract, specification, bill of quantities, construction drawings, extensions and alterations	
Full information found	No information found
2. Continuous history / occupancy	
Complete records and able to confirm good maintenance and no overloading or inappropriate use	No information found

It should be borne in mind that the skills required to research an existing structure and to make a judgement upon its quality of construction may not be widespread within the engineering profession. Desk study research can be time consuming and its outcomes uncertain, thus a commercial decision will generally be made to balance the time an engineer spends in research with the improved information available to her. So, there is a risk of inadequately skilled and trained engineers applying poor judgement based on inadequate desk study research. At this stage, the only ways that this can be accounted for is to (i) make any predictive model and adjustment factors as straightforward and easy to apply as practicable, (ii) limit the impact of any factors relating to desk study information quality and (iii) where possible, provide readily accessible guidance and teaching and learning materials.

7.8 Quality of SDT, NDT and visual inspection information

As the extent of SDT, NDT and visual inspection information obtained for a given timber element varies, so too will the reliability of the estimates of its properties. A range of predictive models have been created based on (a) varying formats of predictor variables (such as (i) knot measure including all four faces of a joist and (ii) knot measure including just the two vertical wide faces) and (b) varying numbers and combinations of predictor variables (such as (i) just knot measure, (ii) knot measure and density, (iii) knot measure, density and SoG).

It is considered that the adjusted model estimates of MoE_{LCL} and MoR_{LCL} reflect the extent and quality of information from in situ appraisal and no further adjustments are needed in relation to the extent of information gained from site. Additionally, for some predictor variables and their combinations, their predictive power is so low that they are not recommended for use.

7.9 Fungal and insect attack

Fungal and insect attack can lead to a reduction in the mechanical and physical properties of an in situ timber. NDT, SDT and visual inspection are able to detect and define deterioration to a good degree and so it is assumed that the damage can be accounted for by using reduced section sizes based on the timber not significantly weakened by the attack. This is the approach recommended in EN17121.

Additionally, where some slight deterioration of the mechanical and physical properties has occurred, then an assumption is made that the changes would be apparent in reduced values of SDT and NDT results. Predictive models based solely on visual inspection (which may not detect minor deterioration) should be suitably conservative. Thus, no further adjustments to the models are needed and although the investigation of possible fungal and insect attack on existing in situ timber is clearly a requirement, it is not considered specifically in this thesis as an additional factor in estimating mechanical and physical properties.

7.10 'Prior grading' and three different models

7.10.1 Introduction to prior grading

As visual grading standards and strength classes relate to sets of pieces and not to individual pieces, the possible occurrence of the prior grading of a set of pieces could affect assumptions made about the distribution of properties of that set of pieces. Applying a model based on the distribution of an entire set of joists (or several entire sets of joists) could under- or over-estimate the mechanical and physical properties of timber joists from a different set of joists which had been affected in some way by prior grading. The use of regression models with multiple predictor variables tends to reduce the effects of prior grading in comparison to sample distribution models, however, it is important that the effects of prior grading are accounted for.

The term prior grading is taken to mean the removal of a sub-set of timber elements from a group of timber elements, in such a way as to affect the distribution of one or more of the mechanical and physical properties of the group. For instance, if a sub-set of the densest 20 timber elements were removed from a set of 100, the remaining 80 timber elements would, as a sub-set, have a lower mean density and reduced standard deviation and hence a different distribution, when compared to the original set of 100. Prior grading could take place for several reasons: (i) the application of an appearance or strength grading process or (ii) through choices made by a client or architect, or carpenters on a construction site, (iii) for economic reasons, whereby a building contractor buys only the cheapest timber for a new property or for instance (iv) due to shortages of timber for political reasons, such as war.

Even prior to the felling of trees in a forest, forestry practices such as selective thinning take place which are a form of sorting. Following the felling of trees in a forest and the processing of structural timber elements, some further sorting will have also taken place to leave only roughly rectangular, adequately sized and complete sections. If these are then used as a sample of timber for laboratory testing, then further sorting will take place to create a sample that can be measured and tested in a way consistent with other samples. So, distorted joists may be removed along with those with significant wane (particularly at bearings) and any joists suffering from collapse due to kiln drying, etc. The remaining sample is termed 'ungraded' as, despite undergoing sorting, it has not undergone a formal grading process.

In this thesis, the term 'prior grading' is used to indicate that ungraded timber has undergone a sorting or grading process to remove elements on the basis of one or more of the issues discussed above. As well as the more obvious forms of prior grading discussed above, two other forms are described below, illustrating the difficulties in ascertaining the extent of prior grading for a given existing structure.

7.10.1.1 Prior grading and year of construction

The range of structures containing structural softwood timber in the UK extends in time to beyond the 17th century. When the current population of in situ structural timber elements is considered, it is seen that this is drawn from a range of forests and species that have changed over time. First growth forests have vastly diminished in this period and some previously common species have become rare, such as longleaf pine in the USA.

So, although not technically prior grading, a time-based selection process has inevitably taken place which now limits the range of wood available to the timber industry when compared to past centuries. This selection process is commonly considered to have generally led to currently available timber being weaker and less stiff and less dense than previously available timber. This is complicated by the improvements in timber quality due to tree breeding programmes which formally began in the 20th century and ongoing changes in forestry practices. It is not known how much the changes in the overall quality of the wood supply would affect the outcomes of a predictive model based solely on 'new' joists and applied to 'old' joists and so this is a topic that requires further investigation.

7.10.1.2 Prior grading and order of construction

The supply of structural timber, from forest to mill, to seasoning, to woodyard and then to site is followed by the carpenters and joiners on site choosing individual pieces of timber from the site supply, as work proceeds from foundations up to the roof of a structure. Thus, a further, informal sorting process occurs as site supplies are picked through and used and replenished. This is impossible to quantify and is especially important when considering limited sampling and testing of timber elements from substantial structures such as a mill or multi-storey terraced residential properties.

In these situations, it is likely that a decision must be made regarding what to do about the effects of possible prior grading on a set of in situ timber elements present in a given structure. This is a question that cannot be answered in this thesis and given its potential importance, it must be a future research question to be addressed by others.

It is worth noting that no formal prior grading of the minor species sample has taken place but all samples of old timber from existing buildings will have undergone some form of prior grading. Thus, care must be taken when joining up the research data in the future to create an expanding data set used as a basis of the ever-improving predictive models.

Three similar but different models are discussed below in relation to the way that prior grading affects them.

7.10.2 Model for in situ individual design

This model would be applied to an individual in situ timber element within an existing structure. This is the model under development in this study and the issue of prior grading is first considered in principle to understand it better and then notional prior grading is applied to the minor species data set to see its effects. The many other issues that relate to this topic such as the need for further contextual information also apply to the two other models in the following two sub-sections.

The methods used in prior grading are only briefly touched upon in this thesis. The extent of prior grading and the methods used (at each step, from forest to completed structure) is likely to be unknowable in most instances for in situ timber. Nevertheless, rough estimates can be made, such as that: (i) the timber in a prestigious structure will have undergone prior grading, removing 'low quality timber', for instance knotty joists and that (ii) the timber used in a modest, speculatively financed building will have undergone prior grading, being bought from a stock of cheaper timber sorted and unable to be sold for higher prices, i.e. removing 'high quality timber'.

Prior grading only changes the weighting of data points within a distribution and does not extend its overall size but bearing in mind the overlapping distributions of softwood species even with different mean strengths and mean stiffnesses, this can still be significant. Potentially, prior grading could change the distribution of data points such that for a single species, the difference between the distributions of the ungraded and prior graded timber may be as much as the difference between the distributions of that species with another.

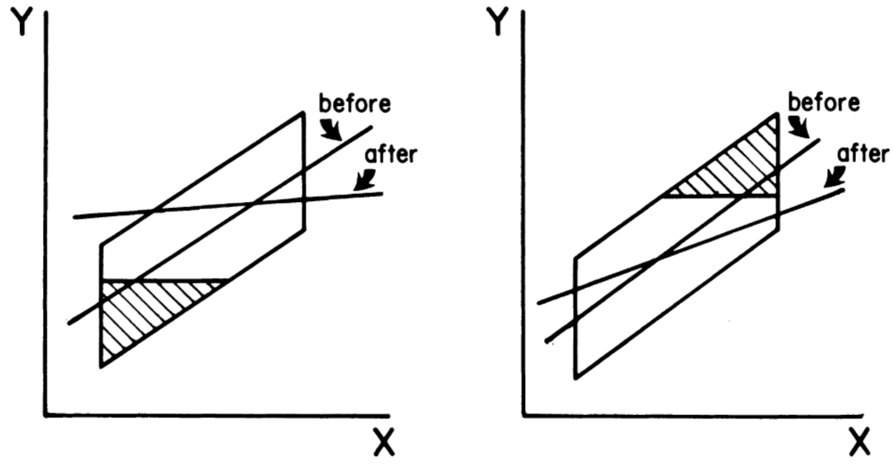

Figure 7.4. Schematic diagrams showing the effect of prior grading extracted from Berk (1983, p. 389)

Initially, prior grading is considered in relation to its effect on the distribution and its OLS regression line. In Figure 7.4, the left hand graph shows systematic removal of data points with low Y values (X is the independent variable and Y is the dependent variable). For this distribution, the mean of the data points increases (for both X and Y), the slope of the regression line is reduced and its intercept increased. This is indicative of timber specified and selected for use in a prestigious building.

In Figure 7.4 the right hand graph shows the opposite effects (to the left hand graph) as data points with high Y values are removed. This is indicative of timber bought and used in a modest, speculatively financed building.

The schematic diagrams are useful to help to understand the effect of different types of prior grading (based on different parameters, e.g. knot measures or density). Another effect could be that the regression line simply shifts upwards after prior grading (remaining parallel with the original regression line), this suggests that prior grading has led to the uniform removal of data points below the entire length of the regression line.

MoE_{dyn} is plotted against MoR in Figure 7.5, which shows the effects of removing just the best and then just the worst 20% of data points based on the knot group measure kg3 (kg3 is chosen as it is a simple indication of the number and size of knots and thus relates better to appearance grading than say kc3). For the mean, the rotation of the blue regression line following the removal of the best 20% of data points shows the effects of that prior grading to be similar to Figure 7.4 right hand side. The roughly uniform vertical shift upwards of the red regression line following the removal of the worst 20% data points shows the uniform removal of data points below the length of the regression line. Thus, kg3 is seen to differentiate the strongest joists better than the weakest ones.

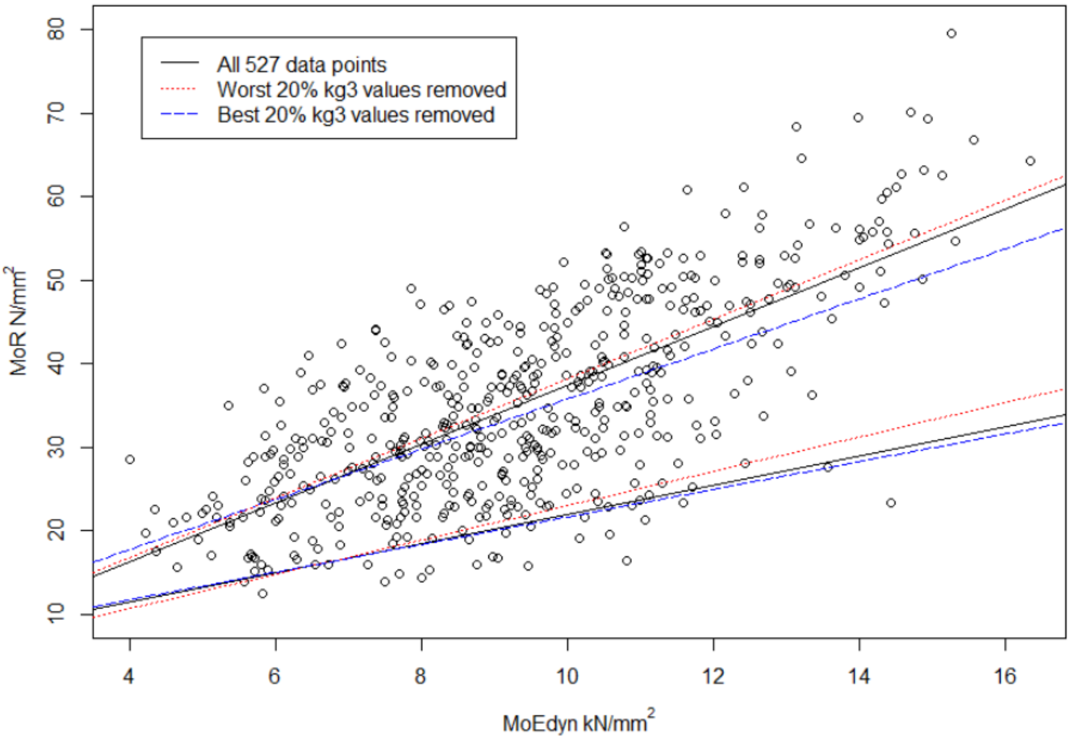

Figure 7.5. MoE$_{dyn}$ plotted against MoR, with median and 0.05 quantile regression lines, showing the effects of prior grading based on the knot measure kg3

The effect of prior grading by removing poor quality joists might be expected to be greater on the 0.05 quantile rather than the mean or the median. For the MoR 0.05 quantile, the effect of prior grading by removal of the best joists (based on kg3) is much reduced (compared to the mean) and the effect of prior grading by removal of the worst joists is much increased (compared to the mean), as expected. It is helpful to understand that the prior downgrading of a sample through removal of the best joists does not lead to large negative changes in the 0.05 quantile regression line as it does for the mean.

The effect of prior grading varies according to its basis. For instance, the removal of joists from a sample based on appearance will create different effects to the removal of say, the least dense joists which would be expected to especially affect density estimation. When this is applied to the estimation of MoR, using density for the prior grading, the effects are almost imperceptible on the mean and for the 0.05 quantile, the results are similar for the removal of both most and least dense joists. The 0.05 regression line rotates slightly clockwise, leading to slightly increased MoR estimates for the less stiff joists and slightly reduced estimates for the stiffest ones.

Figure 7.6 shows the predictive models for density based on the averaged density value from two micro cores, with prior grading by removing the least and most dense timber. The effects of this accord well with the schematic diagrams in Figure 7.4. The upper set of lines relate to the OLS regression for mean density and the lower set relate to the 0.05 quantile of density. The green OLS regression line for timbers remaining after both high and low values are removed is doubly affected by the prior grading and approaches even closer to the horizontal.

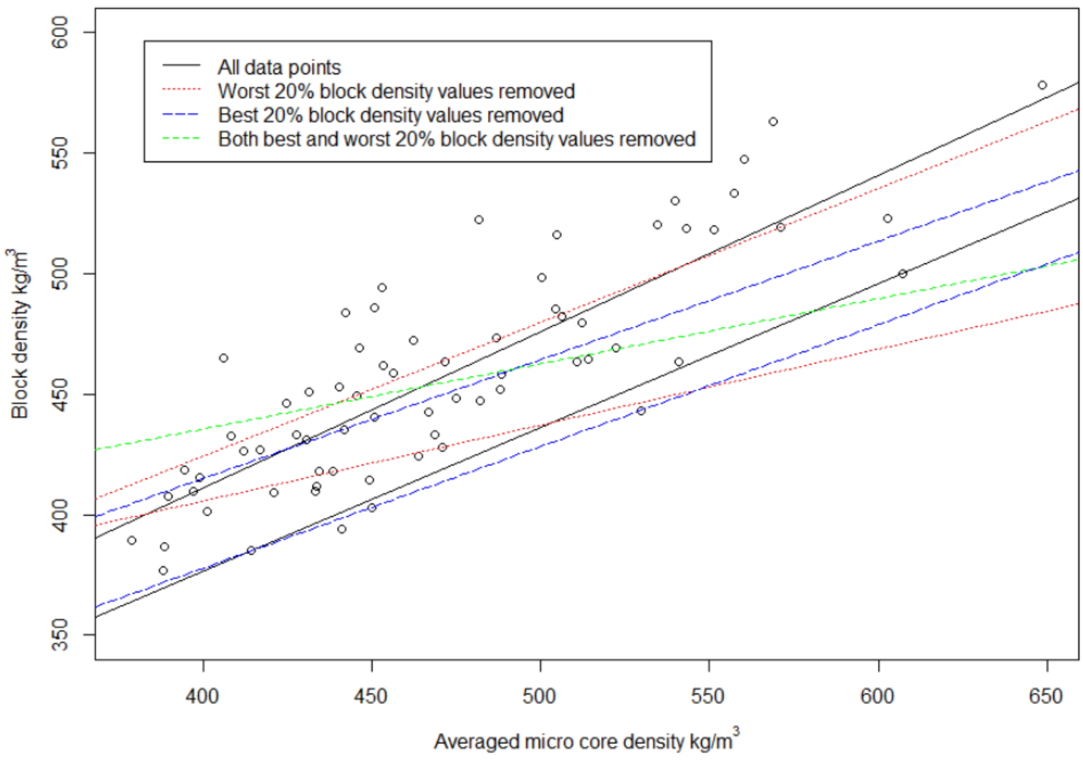

Figure 7.6. Averaged micro core density plotted against block density, with mean OLS and 0.05 quantile regression lines, showing the effects of prior grading based on density

A similar graph, drawn for density, but based on the removal of joists using the knot measure kg3 does not show such marked changes in the regression lines and it is not considered worthwhile to comment further on these effects due to the weak relationship between kg3 and density and the small sample size.

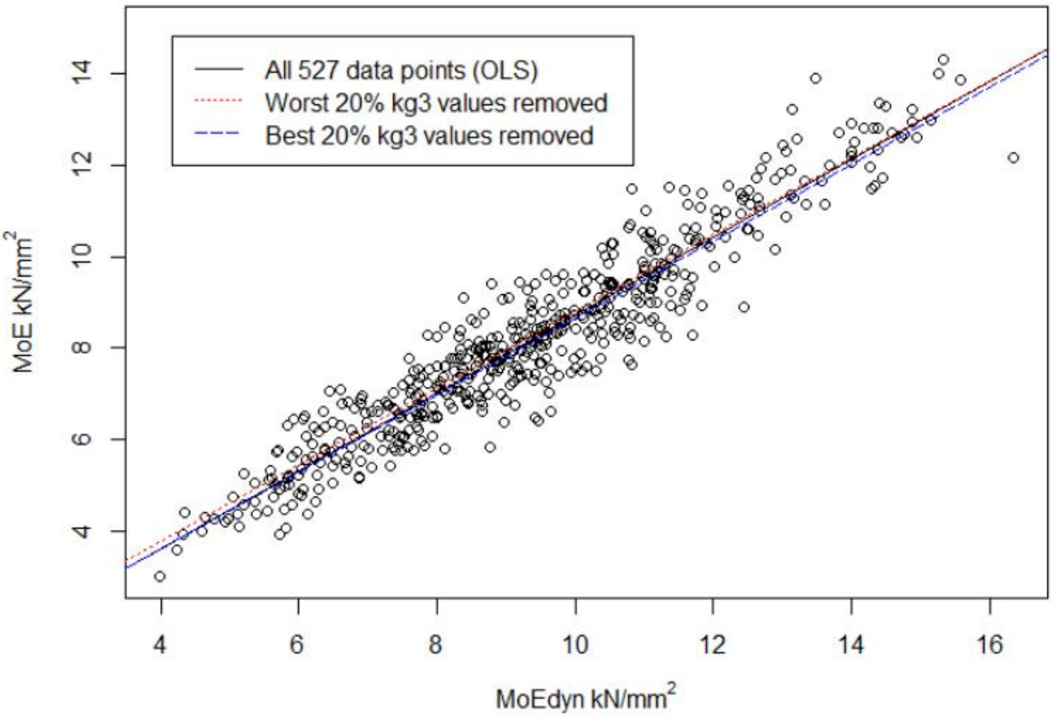

Figure 7.7. MoE$_{dyn}$ plotted against MoE, with mean OLS regression lines, showing the effects of prior grading based on the knot measure kg3

Finally, the effects of prior grading would be expected to be smaller for the estimation of MoE based on MoE$_{dyn}$, due to the high correlation between the two parameters. Using the knot measure kg3, the removal of the best 20% of timber lowers and rotates clockwise the OLS mean regression line by a small amount. Similarly, the removal of the worst 20% of timber raises and rotates the line clockwise by an equally small amount. Prior grading based on density has similar but even less pronounced effects on MoE.

Now, predictive models can be improved from the species-free approach by creating species-specific models for the key species, for instance European spruce or Scots pine. On site, once a species is identified, then these models could be used to estimate characteristic values. Similarly, the current versions of the predictive models assume that no prior grading has taken place. If it is possible to adapt the predictive model at some time in the future to incorporate various types and degrees of prior grading, then on site, if it is possible to estimate prior grading (based on for instance, the desk study, the prestige of the building and the preliminary site inspection) then an appropriately adjusted predictive model could be used to estimate characteristic values.

In order to create ‘prior grading predictive models’, additional research is required to understand the manner and extent of prior grading in different types of structures, during different eras of construction, etc. Notional ‘prior graded’ data sets could then be created; percentiles of data points removed based on the improved understanding of past practices, on the basis of say knots or density, again based on past practices. The ‘prior grading predictive models’ could then be developed using these notional data sets. This work does not form part of this study but is a useful topic area of future research.

Until the additional research is carried out, an alternative to this proposal would be to apply a factor for prior grading (see Section 8.5), which could be applied to predictive models according to the information found on prior grading for a particular structure. For prior grading in structures where high quality timber has been removed at the time of construction, factors could be based on the worst case figures presented below:

(i) for MoR, from Figure 7.5, the worst reduction is in the region of 4%
(ii) for density, from Figure 7.6, the worst reduction is in the region of 7%
(iii) for MoE, from Figure 7.7, the worst reduction is in the region of 1%.

The worst case reductions are read from the extreme right hand side of the graphs and average or typical reductions are smaller. It must be borne in mind that these figures are based on removal of batches of 20% of the data set which is a notional figure. More research is needed to establish the extent of prior grading and then these factors would need reviewing.

7.10.3 Model for salvaged population design

This model would be applied to batches of structural timber elements salvaged from an existing structure during deconstruction. Timber elements would be carefully removed from a structure, de-nailed, sorted into batches and stored, ready for reuse in another project. Thus, this model is affected by damage due to denailing (see Sub-section 2.5). The size and composition of the batches would vary by project according to size and variability of structural form.

For commercial reasons, it is likely that only a sub-sample of timber elements from each batch (or sub-population) are tested. The results from the sub-sample could then be used to estimate the physical and mechanical properties of the remaining timber in the batch. The creation of adequately sized and representative sub-samples from the batches would not be straightforward and prior grading of the timber elements within the existing structure could significantly affect this process.

For any predictive model used, its sensitivity to prior grading could be modelled using software to create notional data sets which replicate the effects of prior grading (such as removal of particularly knotty timber or low density timber). The estimates from the model could then be compared with the estimates from the manufactured data sets. This is beyond the scope of this thesis.

7.10.4 Model for in situ population design

This model would be applied to an existing structure which is intended to be reused and which has large numbers of structural timber elements whose structural function is similar, and whose size and span and loading is similar, for instance, a four storey textile mill building whose structural form comprises many bays which repeat along the length of the mill and from one floor to another. It would be uneconomical to test each joist in each bay at each floor level for a timber floor in this situation and instead a sub-population would be defined and an adequately sized representative sub-sample from it would be tested and its results extrapolated to estimate the properties of all joists in the sub-population.

Similar difficulties arise for this model as for the previous one: (i) the definition of each sub-population, (ii) the choice of sub-sample and (iii) the creation of a model to estimate the properties of all other timber elements in the sub-population. Also, similarly, prior grading would be expected to make this process more complex and once again its effect could be investigated using modelling of manufactured notional data sets of prior graded timber elements. It may be that, on site, possible prior grading could routinely be investigated by creating and investigating a number of sub-samples in a systematic way.

7.11 Factors

From all of the above, it is clear that all predictive models need to be adjusted to account for additional factors. Firstly, a summary is given of the relevant factors and secondly, the ways that the factors could be applied are briefly discussed.

7.11.1 Summary of adjustment factors

Presented in Table 7.4 are suggested factors to be considered to be applied to the predictive model.

Table 7.4. Factors for consideration to adjust the predictive model

Factor	Reqd	Comments
SAMPLE SELECTION for differences between the model (based on a limited sample) and an individual timber element of particular species, growth area and era	Yes	In order to be sure that the model will be safe, a general factor is required to account for sample selection. In due course this will be superseded by a sample selection model.
NUMBER OF AND SIZE OF SAMPLES	No	No further requirement to account for this
QUALITY OF EXISTING STRUCTURE ranges from low to high	No	Indicative of prior grading – see factor below. High quality construction is likely to lead to improved estimated values of the model *
SERVICE LIFE including cycling moisture content or overloading, etc.	No	Where this is known or suspected, values of properties may be reduced *
MECHANICAL DAMAGE due to nails and fixings, notches and rough treatment, etc.	Yes	Beyond reducing cross sectional dimensions due to holes, cuts and notches, account must be taken of general levels of damage to timber elements for MoE and MoR
QUALITY OF DESK STUDY INFORMATION ranges from low to high	No	High quality desk studies give greater certainty and improved confidence, even if only small in effect
QUALITY OF NDT, SDT, VISUAL INSPECTION RESULTS ranges from low to high (and from minimal to comprehensive in extent)	No	The predictive models are adjusted to account for the extent of information inputted into the model
FUNGAL AND INSECT ATTACK INSPECTION RESULTS	No	A simple factor is unable to represent the complexity of outcomes of investigations of this nature. Instead, engineering judgement must be applied, for instance reducing the effective cross section of a moderately affected joist
PRIOR GRADING	Yes	Where prior grading is suspected to have removed 'better' quality timber elements, then a predictive model could over-estimate MoR, density and MoE

*reduction of the mechanical and physical properties of in situ timber elements is assumed to be detected by the NDT, SDT and visual inspection results

7.11.2 Proposals for adjustment factors

In place of standalone adjustment factors, adjustments could be incorporated within the model itself; for instance, as adjustments to the values used in the steps in the calculation of the characteristic values:

1. The mean for MoE or 5 percentile values for density and MoR
2. The lower two sided 50% confidence limit for the mechanical and physical properties

For example, in place of the 0.05 quantile value for density and MoR, the 0.02 quantile could be used; or in place of the lower two sided 50% confidence limit, the lower 95% confidence limit could be used. This would be relatively easy to incorporate in the predictive models. This approach is not proposed for a few reasons:

1. It does not directly address the issues at hand
2. If the required adjustment is large, then an adjustment to the confidence limit value would be relatively small and may well be insufficient to adequately adjust the model.
3. The suggested adjustments would introduce a departure from the Eurocodes, which even if justified, would create new problems of harmonisation.

Thus, at this stage in the model building, just three standalone factors are proposed relating to sample selection, mechanical damage and prior grading. Additionally, these factors must be applied differently for each property of the timber. It is noted that there is some overlap between these three factors and as the sample model (of the sample selection model) is expanded to include samples subject to mechanical damage and prior grading, the need for three separate adjustments will reduce.

7.11.3 Possible use of a decision support system

The three factors described above do not represent well the complexity of the contexts of the appraisal of in situ timber elements and the influences on the properties of the timber. As more research is completed in this topic area, then an attempt could be made to create more complex predictive models that could make sense of all of these influences and bearing in mind its complexity, then a decision support system could potentially be used to help structural engineers to make sense of this.

In brief, a decision support system (DSS) is a computer programme to support decision making which typically analyses and synthesises complex data to produce reports. DSS are typically used in business planning by managers and they have been used in forestry planning for decades (ForestDSS Community of Practice, 2015). They have also been used in health care as clinical decision support systems (CDSS) which are used to assist clinicians to analyse patient data to reach diagnoses.

From the above, the potential use of a DSS in the estimation of the characteristic values of in situ timber merits consideration. A DSS could be created to integrate the two types of data that a structural engineer would obtain: (i) data measurements made on site (in the form of MoE_{dyn} values, knot measures, SoG, density, etc.) and (ii) contextual data (such as the age and location of the structure, the type of structure and the location of the timber elements within the structure, previous uses and knowledge of periods of lack of use, etc.). Working in this way, a DSS could mirror the approaches of CDSS which help practitioners to reach a diagnosis based on a range of observations.

CDSS are used to prevent errors, improve quality, reduce costs and save time and there is evidence to show that they can be extremely effective (Wright and Sittig, 2008). Despite the evidence of improving quality of care, these systems are not widely used outside large academic medical centres and the like. Problems with CDSS can relate to the high cost to create and maintain them and difficulties integrating with computer systems holding a range of information coded in a variety of ways (Corporate Finance Institute, no date).

Ideally, a DSS for in situ timber would include an ever-growing database of the mechanical and physical properties of timber from several centuries (which has been tested and reported on in a coherent way), of all relevant species and from all growth areas, with varying sizes of test pieces. It is important to create as large and complete and consistent a database as possible to improve the predictive models and their estimates. Despite the benefits to be gained by creating a DSS computer programme to combine the objective numerical data with the subjective and contextual data, this would be difficult and the benefits may not be considered sufficient to outweigh the costs of doing this.

If finance or motivation, etc. is not available to create a multi-faceted DSS for the estimation of the mechanical and physical properties of in situ structural timber elements, then the protocol described in Chapter 9 could still be used. This could be developed in time to be similar in nature to the British Standard codes of practice used by structural engineers in designing structures, with flow charts, tables, predictive equations and scope for engineering judgement.

7.12 Non-compliance with the Eurocodes

Although efforts have been made to create predictive models that comply with the harmonised standards of the Eurocodes, it is clear that the methods to obtain the characteristic values of MoE, MoR and density differ. There is however an exemption written into the Construction Products Regulations that allows for some flexibility if a process can be shown to be trustworthy or otherwise shown to work, and the product is not intended for the open market. It is hoped that this thesis can be seen as a first step in the demonstration of a method that works in estimating the mechanical and physical properties of individual in situ structural timber elements and that the level of assurance is equal to currently accepted methods that are applied to new timber. Incidentally, as the predictive models apply to timber elements that are to remain in situ (and so are not destined for the open market), this is another distinction between assessing in situ timber and assessing salvaged timber (and assessing 'new' timber).

7.13 Conclusions

In this chapter, the factors affecting the predictive models are discussed and proposals are made to address these. The most important issue is sample selection bias, which in the long term requires a sample selection model to be built. In the short term an adjustment factor is recommended to be applied to the predictive models to account for this issue. Several other influencing factors are also discussed (together with associated proposals to address them), such as: service life, mechanical damage, fungal and insect attack and prior grading. Additionally, adjustments to the model are discussed in relation to contextual information such as: quality of existing structure, quality of desk study, information and quality of NDT, SDT and visual inspection results.

The identification of firstly, the key factors affecting the predictive models (selection bias, prior grading and the deterioration of wood during its life in service) and secondly, the most appropriate statistical methods of accounting for these factors is a unique contribution to knowledge.

This broader discussion leads to several issues that are beyond the scope of this thesis, but that require further research to develop the predictive models of this study and are commented upon a little further in Chapter 9. In the following chapter, the building of the predictive models for MoE, density and MoR is described.

Chapter 8 Building the predictive models

8.1 Introduction

The first purpose of this chapter is to summarise and discuss the building of predictive models for the determination of the lower two sided 50% confidence limit of the mean of MoE (MoE_{LCL}) and the 5 percentile (or 0.05 quantile, as it is generally referred to here) of density (termed density ρ_{LCL}) and of MoR (termed MoR_{LCL}) for individual joists based on the outcome of SDT, NDT and/or visual inspection. The 'best' multivariate model is built first, followed by other multivariate models and a series of models based on single predictor variables, where possible. Methods of adjustment for those models based on the weaker predictive variables are determined and adjusted models are derived. Models firstly, are verified, where possible, using a new data set based on Sitka spruce and secondly, are compared with the visual grading and strength classification methods to determine characteristic values of MoE.

When assessing a model on site, it may not be possible to measure each of the predictor variables in the 'best' multivariate model. For instance, on site, it may not be possible to remove a ceiling and only limited or difficult access may be available to see, for example, just the two vertical wide faces of in situ joists. Thus, variants of the predictive model are explored with different and sometimes inferior predictor variables which could still prove useful in practice. Details of the model building are given in three separate appendices for each of the three properties, as similar but different approaches were followed.

The second purpose of this chapter is to tie together many elements of the thesis with a short protocol that describes how the predictive models for the lower two sided 50% confidence limits could be applied in practice to determine characteristic values.

Unique contributions to knowledge described in this chapter are:

(i) the application of quantile regression and bootstrapping (to find the confidence intervals around quantiles) to timber data in order to create two of the three the predictive models
(ii) the development of a methodology for the creation of new predictive models for the appraisal of the properties of in situ timber in accordance with the Eurocodes.

8.2 Building the models for MoE_{LCL}

The model for MoE_{LCL} is based on OLS regression and includes the following steps: (i) choose useful predictor variables, (ii) review the relationships between the predictor variables, (iii) check the underlying assumptions of the regression and then carry out any necessary corrective measures, (iv) potentially refine the model by considering polynomial variables (such as $\sqrt{x}\ \ and\ \ x^2\ and\ \ln x$ in place of just x), (v) consider interactions between variables, including outliers and influential points, (vi) assess the predictive power of models with different predictor variables and (vii) adjust the weaker models to improve their potential for use. Details of the process are given in the appendices.

8.2.1 MoE_{LCL} – model based on single predictor variables

It is straightforward to derive the OLS regression trendlines relating single predictor variables and MoE. From these, the equation for the linear estimate of the lower confidence limit can be derived and Table 8.1 summarises the results of several of the better single predictors of MoE_{LCL}. It is seen that the range of estimates of MoE_{LCL} for

MoE_{dyn} is almost twice as wide as for density and the knot measures kg3, kg10 and kg11. kg10 was not expected to be a better predictor than kg3 and its greater range is thought to be a quirk of the small data set. SoG's range is particularly small, showing its weakness as a predictor.

Table 8.1. Maximum and minimum values of the 50% two sided lower confidence limits of MoE (kN/mm^2) for six grading measures

	Min confidence interval	Min 50% LCL	Max 50% LCL	Range of LCL
MoE_{dyn}	0.04	3.54	14.06	10.52
Density	0.04	5.41	12.58	7.17
SoG	0.04	6.55	8.45	1.90
kg3	0.04	4.52	9.80	5.27
kg10	0.04	3.66	9.75	6.09
kg11	0.04	4.94	9.32	4.38

It is seen that although SoG is the weakest predictor, its lowest prediction of MoE_{LCL} is higher than all others. Thus, some adjustment of these equations is needed. Several standard statistical techniques were considered and investigated, but none of these were considered to adequately deal with the issue. After considering several non-standard methods, finally, an adjustment method using a new intercept based on a datum and keeping the highest point of the original linear estimate was considered as being conservative without being overly punitive.

There is a complex interaction between the variables, and the relationships are particularly weak between MoE_{LCL} and SoG and between MoE_{LCL} and the individual knot measures. When the suggested adjustments are checked by plotting observed values of MoE along the x-axis, it is seen that these weaker measures are not satisfactorily reduced. Figure 8.1 shows how the linear estimates for MoE_{dyn} and density adjust well with the approach above, however, SoG and the knot measures have such weak relationships with MoE that even with their adjustments, they are still prone to over-prediction.

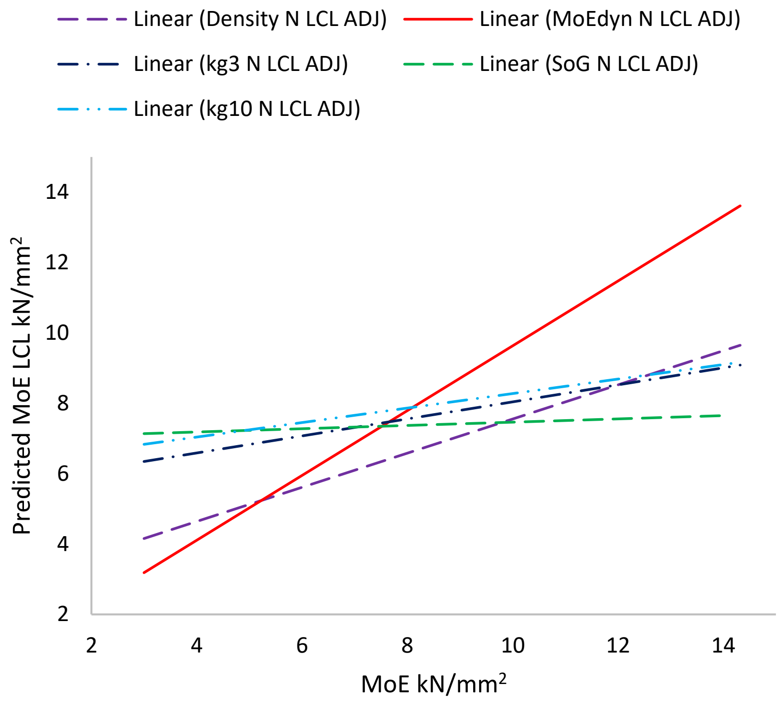

Figure 8.1. Adjusted linear estimates for MoE_{LCL} with measured MoE on the x-axis

Although all adjusted models are presented below, it is important to face up to the inadequacy of some predictor variables to differentiate MoE_{LCL} enough to be used in practice. Referring to the literature and to Figure 8.1, it appears that no amount of adjustment will change measured SoG readings on their own to usefully predict MoE_{LCL}. Thus, in Section 8.5, a star rating system is employed to differentiate between models and with only a one star rating, SoG is not recommended for practical use.

Equations of the adjusted linear estimates of the 50% two sided lower confidence limit of MoE (MoE_{LCL}) for the predictor variables considered are presented below:

$$Adjusted\ MoE_{LCL} = -0.2512 + 0.8758\ MoEdyn \quad (8.1)$$

$$Adjusted\ MoE_{LCL} = -6.8456 + 0.0336\ density \quad (8.2)$$

$$Adjusted\ MoE_{LCL} = 9.7545 - 4.5596\ kg10 \quad (8.3)$$

$$Adjusted\ MoE_{LCL} = 9.7960 - 5.7488\ kg3 \quad (8.4)$$

$$Adjusted\ MoE_{LCL} = 8.8467 - 0.2796\ SoG \quad (8.5)$$

8.2.2 MoE_{LCL} – Multivariate 'best' model

Based on the limited data set and from the statistical tests used (calculating the coefficient of determination and its adjusted value, the Mallows Cp statistic and Akaike's Information Criterion), there is little to choose between a variety of combinations of predictor variables: MoE_{dyn} , MoE_{dyn} + kg3, MoE_{dyn} + kg3 + SoG, MoE_{dyn} + kg3 + SoG + Dens. This strengthens the argument for creating a range of predictive models which can be applied according to the needs of a structural appraisal. As the predictive models' data set is expanded in the future, the relative power of different models can be reviewed. The final 'best' multivariate model for mean MoE combines MoE_{dyn} + kg3 + SoG.

$$\begin{aligned} &Estimated\ mean\ MoE \\ &\qquad = 0.979 + 0.820\, MoEdyn - 1.065\, kg3 - 0.038\, SoG \end{aligned} \tag{8.6}$$

Next, the lower two sided 50% confidence limit (LCL) for this model is determined, giving the equation below, which is used to predict the characteristic value of MoE.

$$MoE_{LCL} = 0.947 + 0.820\, MoEdyn - 1.072\, kg3 - 0.040\, SoG \tag{8.7}$$

Reference should be made to Section 8.5 to see how MoE_{LCL} is used to determine the characteristic value of MoE.

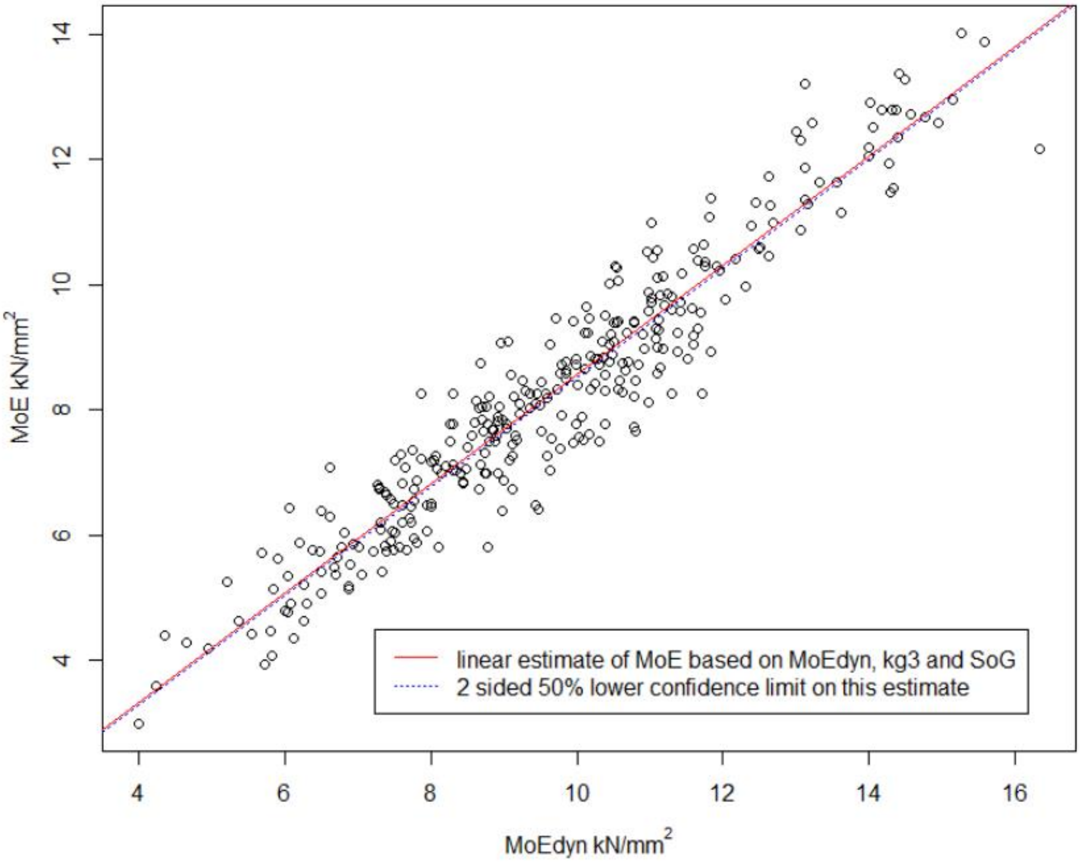

Figure 8.2. Scatter plot of data points (red line is the linear estimate of MoE based on MoE_{dyn}, kg3 and SoG, blue line is the 2 sided 50% lower confidence limit on this estimate, MoE_{LCL})

Reference to Figure 8.2 shows how narrow the confidence interval around the estimated mean MoE is in relation to the scatter of the data points. A confidence interval is not generally linear, it typically narrows close to the mean, where the error in the model is at a minimum. However, as the trend line for MoE mean is linear and the lower confidence limit is so close, the degree of curvature is nominal and a linear equation provides a straightforward estimate for the lower confidence limit.

8.2.3 MoE_{LCL} – Multivariate other models

To illustrate the range of combinations of predictor variables, three more combinations are considered in relation to the 'best' model which uses MoE_{dyn}, kg3 and SoG. The 'best' model for MoE_{LCL} has an adjusted $r^2 = 0.912$

$$MoE_{LCL} = 0.947 + 0.820\, MoEdyn - 1.072\, kg3 - 0.040\, SoG \tag{8.8}$$

The three other models are as follows, with adjusted r^2 values of 0.897, 0.538 and 0.314 respectively

$$MoE_{LCL} = 0.613 + 0.876\, MoEdyn - 0.002\, density \quad (8.9)$$

$$MoE_{LCL} = -0.335 - 4.234\, kg3 + 0.03\, density \quad (8.10)$$

$$MoE_{LCL} = 11.003 - 5.544\, kg3 - 0.112\, SoG \quad (8.11)$$

The first of these models includes the strong predictor MoE_{dyn} whereas the other two models include variables that are relatively easy to measure on site: the knot measure and slope of grain (by visual inspection) and density (by coring and weighing the extracted cores). The loss in power of the models based on the simpler site investigation work may be acceptable in some commercial situations.

Just as for the predictive models based on single variables, those models that exclude MoE_{dyn} are not conservative for MoE values below around 8 kN/mm^2. The same discussion around penalizing the weaker single predictor models holds true for the weaker multivariate models too. Similar approaches are proposed which, while leading to conservative estimates of MoE, should prove acceptable to structural engineers. These adjustment methods are described in the appendices and the adjusted predictive models are presented below

$$Adjusted\ MoE_{LCL} = -3.2734 - 4.2353\, kg3 + 0.03008\, density \quad (8.12)$$

$$Adjusted\ MoE_{LCL} = 11.0035 - 6.2493\, kg3 - 0.1121\, SoG \quad (8.13)$$

8.2.4 Use of MoE_{LCL} models on Sitka spruce data

The predictive models developed with and based on the four minor species are applied to a data set of Sitka spruce (n=60). The Sitka spruce data set has been visually graded in accordance with INSTA142 and joists are graded between T0 and T3. Applying EN1912 in an approximate way, these visual grades equate to strength classes from C14 to C30, with characteristic values of MoE ranging from 7 to 12 N/mm^2.

The graph in Figure 8.3 shows the data points of predicted MoE_{LCL} (i) based solely on the adjusted MoE_{dyn} predictive model ('MoEdynADJ') and (ii) based on the unadjusted predictive model using MoE_{dyn} and density ('MoEdynDens'). The first model, based on a single predictor variable, is seen to be conservative for Sitka Spruce and this is considered to be due to the sample selection issues discussed in Chapter 7. The multivariate model appears to have reduced the effects of sample selection as its predicted data points are closer to the actual measured values.

Pairs or triplets of data points can be identified on the graph, joined by a common value of MoE_{dyn} and colour (i.e. visual grade). The straight lines of both the estimates are seen to match well with the slope of the measured values of MoE and are seen to be conservative.

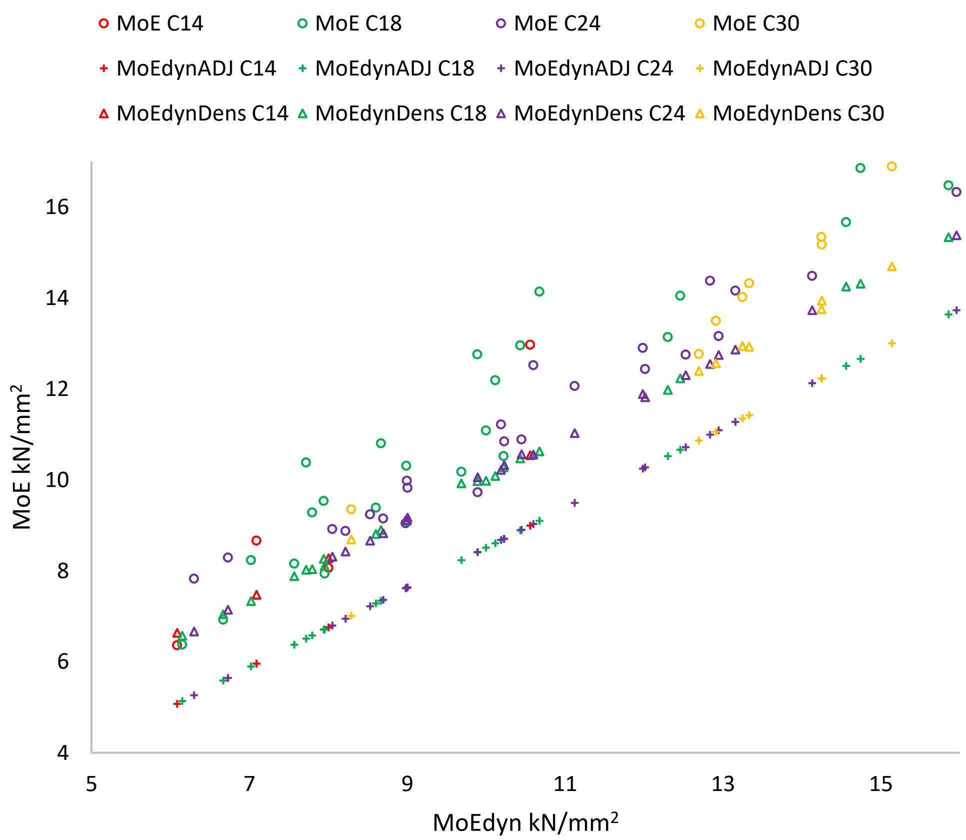

Figure 8.3. Measured MoE values and adjusted estimates of MoE LCL based on MoE_{dyn} for Sitka spruce (n=58)

The key conclusions from this limited verification exercise are: (i) the predictive models based on the four minor species appear to work (conservatively) with a Sitka spruce data set, (ii) the combining of predictor variables appears to improve the models' transferability between species, (iii) much work remains to be done to address the limited size of the study data set and deal with sample selection issues and (iv) the predictive models work better than visual grading and strength classification.

8.2.5 Comparison with visual grading codes

The efficacy of the predictive models can be compared both with the visual grading codes and with the actual values of MoE obtained from testing. This is already done for Sitka spruce in Figure 8.3 above. In Figure 8.4 below, the visual grading code BS4978 is used which directly relates to the minor species data set and roughly divides up the joists into thirds: Reject (no strength grade classification and so undefined characteristic MoE), GS (C14 with characteristic MoE = 7 N/mm^2) and SS (C18 with characteristic MoE = 9 N/mm^2).

The 'best' model (MoE_{dyn}, kg3 and SoG) (n=317), predicting MoE_{LCL} , is compared with strength classifications in Figure 8.4, with MoE_{dyn} on the x-axis and MoE on the y-axis. Measured MoE data points are also shown on the graph (as grey crosses) indicating the spread of actual MoE values for any given value of MoE_{dyn}. The 'best' model has a smaller spread of estimates which represents the ranges of MoE_{LCL} values for given values of MoE_{dyn}.

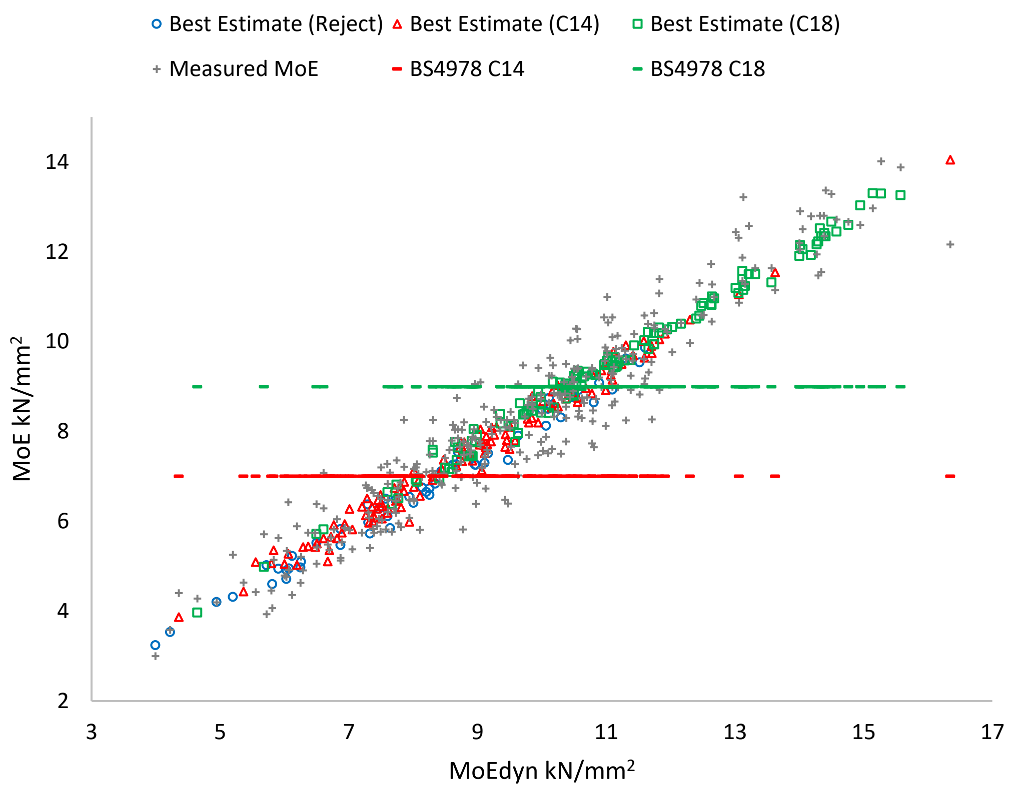

Figure 8.4. Multivariate predictive model for MoE_{LCL} (using MoE_{dyn}, kg3 and SoG) compared with strength classifications. Also showing measured values of MoE.

The blue, red and green strength classifications broadly follow increases in measured MoE, with much overlapping between categories. The associated characteristic mean MoE values of undefined, 7 and 9 kN/mm^2 clearly relate poorly with the actual values of MoE. Breaking down the measured MoE data points into the strength classes of Reject, C14 and C18 adds little of interest, other than to once again show the general trend of increasing stiffness with increasing strength class but with much overlapping of data points.

8.3 Building the model for density$_{LCL}$

The model for density$_{LCL}$ is based on quantile regression and is based on a single predictor variable, which obviates the need for an extended model building process considering the selection of the best of several variables. Details of the process are given in the appendices.

8.3.1 Density$_{LCL}$ – Model based on single predictor variable

Model building for density is based on 68 structural sized joists of western hemlock (*Tsuga heterophylla*) taken from the minor species sample. Two micro clear (6.5 mm diameter 91 mm long) specimens (A and B) were taken from undamaged regions of each joist and the averaged density from a pair of the micro clear specimens is used in the model building. A more detailed description of this work is given in the appendices. It should also be noted that as well as using pairs of micro cores, it is considered that the drill chip extraction (DCE) SDT method, described in Sub-section 6.2.2.5, could also be used to estimate density. As the DCE method requires smaller holes than the micro clear method, it has the advantage of causing less damage to in situ timber.

The density of the structural sized joists is based on a 'block' cut from the joist in accordance with EN408 and adjusted for moisture content in accordance with EN384. This cut section must be free from knots and resin pockets and so is only representative of clear wood within the test piece, as are the micro clear specimens. The correlation of the 'block' density with that of the entire joist is strong (coefficient of determination $r^2 = 0.74$) but will never be perfect in imperfect timber as the two densities are effectively of different materials.

Table 8.2. Correlation summary for 'block' density

	Specimens	r^2
Mass of complete joist	150	0.74
Micro clear A density	68	0.53
Micro clear B density	67	0.68
Mean of micro clears A&B	67	0.70

The pros and cons of using quantile regression analysis to determine the 0.05 quantile are discussed in detail in Chapter 3 and in the appendices. The chief reason for its adoption is its ability to describe the edges of a distribution (where the 0.05 quantile lies) with greater accuracy and robustness than OLS regression. Determining the equation for a 0.05 quantile is relatively straightforward, making use of the quantreg package in R, the predictive model for the 0.05 quantile of the density of an individual joist, based on the averaged density value of two micro clear specimens is

$$Est. 0.05\ quantile\ of\ density = 138 + 0.59\ \times Averaged\ micro\ clear\ density \tag{8.14}$$

Determining the equation for the 50% two sided lower confidence limit of the 0.05 quantile of density, ρ_{LCL} (from which, the 5 percentile characteristic value of density ρ_k can be determined) is a little more complicated and makes use of bootstrapping which is commonly used to generate confidence intervals without having to assume a particular distribution of a data set (Kabacoff, 2015). A more detailed explanation of the model building is given in the appendices. The predictive model for ρ_{LCL} based on the averaged density value of two micro clear specimens is

$$Density\ _{LCL} = 158 + 0.53\ \times Averaged\ micro\ clear\ density \tag{8.15}$$

8.3.2 Comparison with visual grading codes

In Figure 8.5, estimates calculated using the above predictive equation are compared with (i) block density measurements taken from each joist in accordance with EN408 and (ii) characteristic densities determined through visual grading to BS4978 followed by strength classification.

Refer to the graph in Figure 8.5 which includes Reject joists (n=9), C14 joists (n=25) and C18 joists (n=34). The conservative nature of visual grading and strength classification is clear to see, and the C14 and C18 characteristic density values have only a weak and limited relationship with actual values. Ungraded joists are not shown, and the minimum measured block density is 380 kg/m^3.

The model estimates for ρ_{LCL} increase broadly in line with the increasing values of the block density measurements. No estimate exceeds the respective block density value and all estimates (which include all 68 joists and so also include the “Reject” joists) are greater than the characteristic values of visual grading and strength classification.

As expected, the distribution of the model estimates diverges from the block density values at higher densities, where there are fewer data points and variance would be expected to be greater. On average the model estimates are 10.6% lower (49.7 kg/m^3)

than the measured block densities and this reduction increases from 7.7% for the combined lower two quartiles to 13.2% for the upper two quartiles.

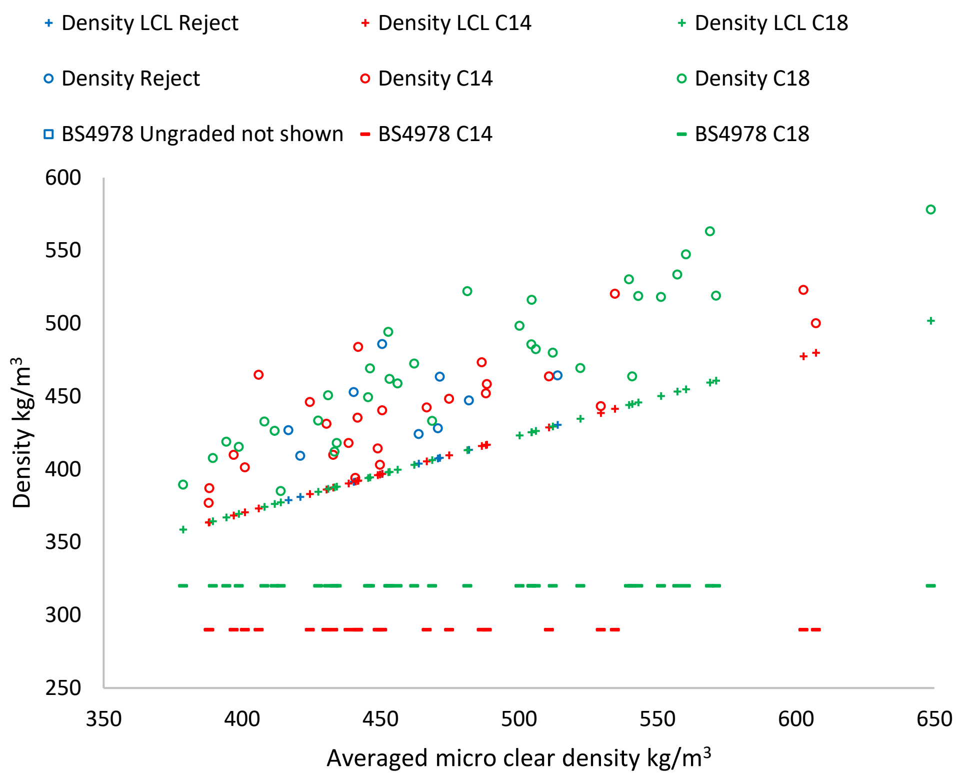

Figure 8.5. Measured 'block' density values and estimates of density LCL based on micro clear pairs for western hemlock (n=68) compared with visual grading and strength classification

In summary, two methods have been developed to allow the density of an individual in situ structural timber element to be investigated (i) by taking a pair of small diameter cores and (ii) by using the DCE method with even smaller diameter drill holes. A linear model has been developed for ρ_{LCL} . Unfortunately, it was not possible to test the predictive model on the Sitka spruce data which does not include any micro clear specimen measurements. Therefore, further work is required to verify the model and to extend its basis, particularly in relation to sample selection issues.

8.4 Building the model for MoR_{LCL}

The model for MoR_{LCL} is based on quantile regression and is more straightforward than the model building for MoE_{LCL}. The best models are found by comparing nested models using ANOVA and using the goodness of fit of the models. Polynomial variables are considered along with adjustment of the weaker models. Finally, the two approaches of OLS and quantile regression are compared in relation to MoR_{LCL}. Details of the process are given in the appendices.

8.4.1 MoR_{LCL} - Model based on single predictor variables

Quantile regression is chosen to determine the 0.05 quantile of MoR for the same reasons it was chosen for density and once again, bootstrapping is used to determine the 50% two sided lower confidence limit of the 0.05 quantile of MoR, termed MoR_{LCL} (from which, the 5 percentile characteristic value of $f_{m,k}$ is determined). The models based on single predictor variables are weaker than the best multivariate models and, as for the equivalent models for MoE_{LCL}, require adjustment to prevent over-estimation and to improve their potential for use in practice.

The adjusted equations are

$$Adjusted\ \ MoR_{LCL} = \ 0.258\ +\ 1.961\ MoE_{dyn} \tag{8.16}$$

$$Adjusted\ MoR_{LCL} = \ -11.451 + 0.065\ density \tag{8.17}$$

$$Adjusted\ \ MoR_{LCL} = \ 23.54 - 20.258\ kc3 \tag{8.18}$$

$$Adjusted\ \ MoR_{LCL} = \ 21.22 - 15.195\ kc9 \tag{8.19}$$

$$Adjusted\ MoR_{LCL} = \ 17.408 - 0.465\ SoG \tag{8.20}$$

All of the above models are rated according to the ranges of their predicted values and only the MoE_{dyn} model is recommended for practical use.

8.4.2 MoR_{LCL} - Multivariate ‘best’ model

Again, based on the limited data set and from the statistical tests used (comparing nested models using ANOVA and comparing AIC values), the ’best’ multivariate model for MoR_{LCL} comprises the predictor variables: MoE_{dyn} + kc3. Transformations of the variables were investigated and the results were marginal and inconclusive, and finally, the simplest model was chosen with no transformations.

First, the equation for the 0.05 quantile is determined and the predictive model for the 0.05 quantile of the MoR of an individual joist, based on MoE_{dyn} and the knot measure kc3 and using the full data set (n=527) is

$$\begin{aligned} &Estimated\ 0.05\ quantile\ MoR \\ &\qquad = 9.301\ +\ 1.799\ MoEdyn\ -14.383\ kc3 \end{aligned} \tag{8.21}$$

Next, the equation for the two sided 50% lower confidence limit is generated using bootstrapping in in a similar way as for $density_{LCL}$. The 'best' predictive equation for MoR_{LCL} generated this way is

$$MoR_{LCL} = 8.07 + 1.78\ MoEdyn - 14.25\ kc3 \tag{8.22}$$

This in turn can be used to determine the characteristic value of bending strength, $f_{m,k}$ for individual joists in situ.

8.4.3 MoR_{LCL} - Multivariate other models

In addition to the 'best' predictive model, here, another multivariate model is developed based solely on density and kc3 to illustrate how other models could also be developed and used. The correlation coefficients for density and kc3 with MoR are +0.499 and -0.480 respectively; they also have a very weak correlation with one another.

The model is developed in a similar way to the 'best' model and for MoR_{LCL} a total of 20 bootstrapped LCL values are used. Here are the two equations determined from this analysis

$$Estimated\ MoR = 5.922\ +\ 0.0528\ Dens\ -21.0603\ kc3 \tag{8.23}$$

$$MoR_{LCL}\ =\ 5.689\ +\ 0.05056\ Dens - 19.8069\ kc3 \tag{8.24}$$

The range of MoR_{LCL} for this multivariate model is 23.45 N/mm^2 which is only slightly smaller than the range of the 'best' model (26.89 N/mm^2), showing that this alternative approach could be useful in practice. Adjustment of this model is carried out in the same way as for the multivariate models for MoE_{LCL} and the adjusted predictive equation uses a datum based on the lowest estimate of MoR_{LCL} made using the 'best' predictive equation MoR_{LCL} = 8.09 N/mm^2.

$$Adjusted\ MoR_{LCL}\ =\ 1.707 +\ 0.05745\ Dens - 19.80\ kc3 \qquad (8.25)$$

8.4.4 Use of MoR_{LCL} models on Sitka spruce data

The graph in Figure 8.6 is based solely on the Sitka spruce data set and shows the measured values of MoR (hoops with colours differentiating between strength classifications based on the visual grades of INSTA142). The overlapping of the groups of differently coloured hoops shows the weakness of the visual grading. Three sets of predicted vales of MoR_{LCL} are presented. Firstly, the 'best' predictive model (MoE_{dyn} and kc3) uses small crosses with the colours differentiating between strength classifications. Pairs of data points can be identified on the graph, joined by a common value of MoE_{dyn} and colour (i.e. visual grade). The trend of the estimates is seen to match well with the slope of the measured values of MoR.

Secondly, along the bottom of the graph the adjusted estimates of MoR_{LCL} based on the single predictor MoE_{dyn} are shown by black triangles. These are seen to be overly conservative and, as for MoE, it appears that: (i) predictive models based on multiple variables appear to transfer between species better than models based on single variables, and (ii) the issue of sample selection remains to be addressed.

Thirdly, also marked on the graph are the estimates of MoR_{LCL} , calculated solely using the Sitka spruce data set, using quantile regression and bootstrapping. These estimates are based on the sole predictor MoE_{dyn} and are shown as solid brown squares. MoE has been chosen for the x-axis (in place of MoE_{dyn}) to illustrate the joggling of the data points of the estimates based on MoE_{dyn} (which otherwise would be aligned perfectly, giving the appearance of greater precision than deserved).

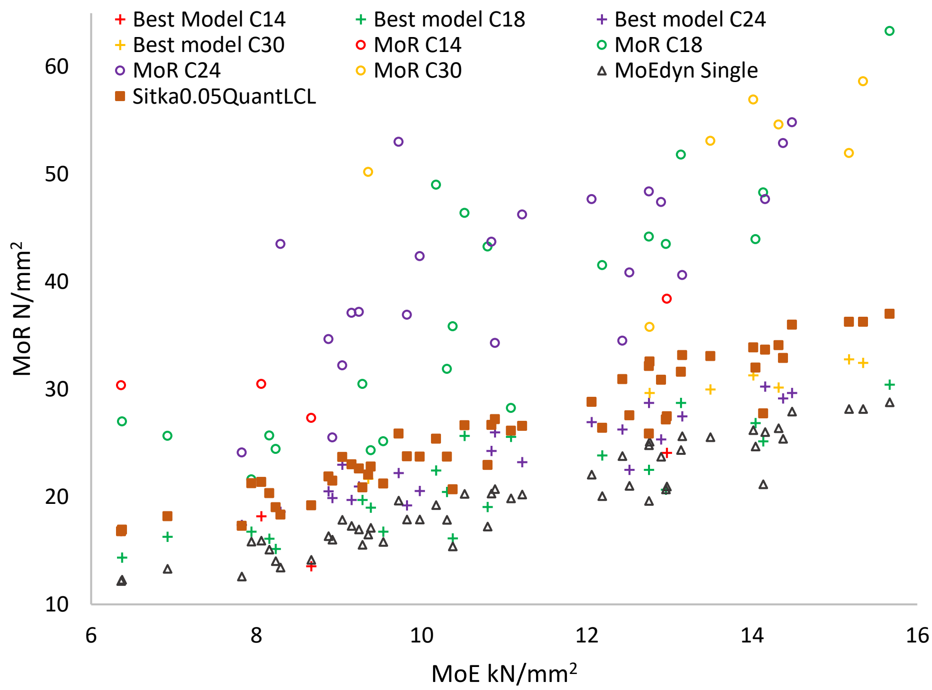

Figure 8.6. Scatter plot of measured MoR data points and model estimates of MoR_{LCL}

Based on the 'best' multivariate model, the predicted values of MoR_{LCL} vary from 13.57 to 35.16 N/mm^2. A similar exercise carried out for a different multivariate model (density and kc3, adjusted) shows a similar pattern but with a reduced spread of predicted values of MoR_{LCL} and which range from 13.41 to 31.60 N/mm^2. Finally, the model created using the Sitka spruce data set, gives a similar but higher range from 16.81 to 40.39 N/mm^2. Thus, differences are apparent due to sample selection, which in this instance are conservative but for other species may not be.

8.4.5 Comparison with visual grading codes

In Figure 8.7, predicted values of MoR_{LCL} (based on the 'best' model, using MoE_{dyn} and kc3) are compared to measured values of MoE differentiated by visual grading carried out to BS4978. The three visual grades of BS4978 relate to the following strength classes: reject (no strength classification and so undefined characteristic MoR, GS (C14 has characteristic MoR = 14 N/mm^2), and SS (C18 with characteristic MoR = 18 N/mm^2).

Measured MoR data points are shown on the graphs (as small hoops, coloured to identify their visual grade) indicating the range of actual MoR values for any given value of MoE_{dyn}. The MoR_{LCL} estimates based on the 'best' model (coloured x) approximately follow the line of the 0.05 quantile of the data set and they clearly diverge from the mean trendline of the measured MoR data points (not shown). They show a breadth of scatter representing the range of MoR_{LCL} values at each value of MoE_{dyn}. The green and red horizontal dashed lines show the estimates based on visual grading.

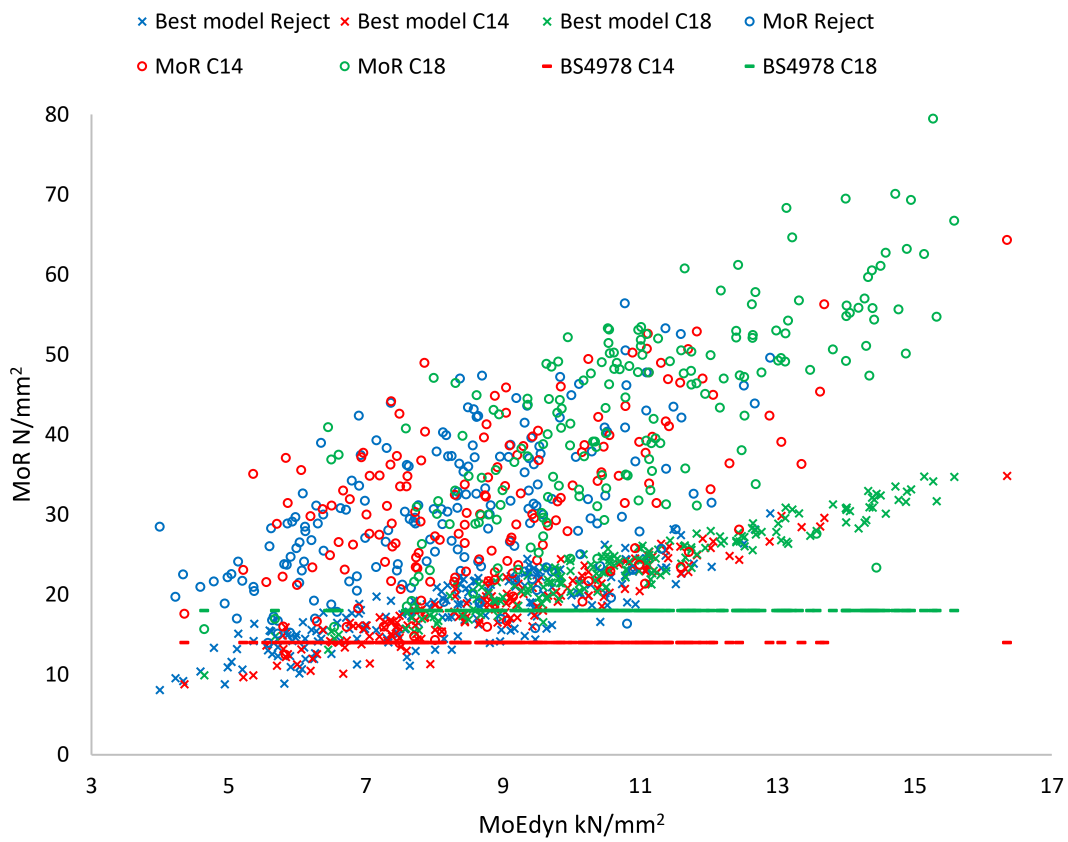

Figure 8.7. Scatter plot of MoE_{dyn} and MoR with measured MoR data points, 'Best' model LCL estimates of MoR and characteristic values of MoR based on visual grading

Here, breaking down the measured MoR data points into the strength classes of Reject, C14 and C18 adds little of interest, other than to once again show the general trend of increasing strength with increasing strength class but with much overlapping of data points.

A second graph is presented in Figure 8.8 to illustrate how an alternative, adjusted multivariate model for MoR_{LCL} (based on density and kc3) fares. Despite the shallower slope and slightly wider spread of the estimates of MoR_{LCL}, this alternative model appears to stand comparison with the 'best' model well. Due to its slight reduction in power, its highest and lowest estimates of MoR_{LCL} are slightly less extreme.

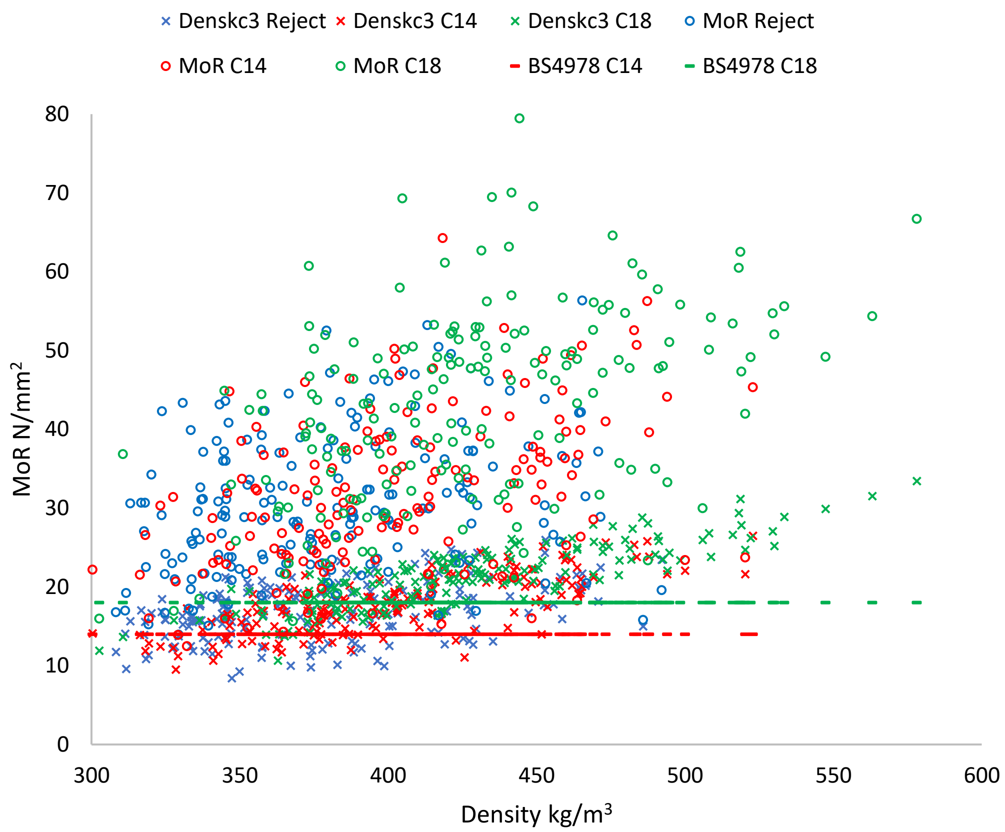

Figure 8.8. MoR_{LCL} as predicted using density and kc3 (adjusted model)

8.5 Protocol for the prediction of characteristic values

Advice on the appraisal of the mechanical and physical properties of timber is provided by the Eurocodes is in the "Guidelines for the on-site assessment of load-bearing timber structures" (CEN, 2019b) which creates an overall framework within which the following protocol can be located as a direct replacement for much of Section 5.6 in which strength classification based on visual grading is recommended. In its place, the characteristic values of the key mechanical and physical properties of MoR, MoE and density should be estimated using the predictive models and factors presented in this thesis.

Once these key characteristic values are estimated then secondary values of mechanical and physical properties can be calculated using the formulae presented in EN384 (CEN, 2010). Discussion below focusses on a beam (adjustments are easily made for a column, stud, etc.) and covers:

(i) what should be measured on site
(ii) use of the predictive models to estimate the lower 50% two sided confidence limits around mean and 0.05 quantiles
(iii) adjustment of the model outputs to obtain characteristic values of mechanical and physical properties.

8.5.1 What should be measured on site

Material characteristic values can be estimated from a range of site measurements and different combinations of site measurements. However, as MoE_{dyn} is the best predictor of both MoE and MoR, best efforts should be made to obtain this particular measurement. For all site measurements, the best measurements available should be taken and an appropriate model can be used to accommodate shortcomings associated with any inferior or missing measurements. Additionally, it is recommended that, where possible, site measurements are carried out under reference conditions, in particular moisture content, as both MoE and MoR vary as this varies from a suggested reference value of 12% (Llana *et al.*, 2014; Íñiguez-González *et al.*, 2015). Where reference conditions do not pertain, then adjustments can be made (using the methods given in EN384). Extreme temperatures may also affect results and so should be avoided or adjusted for.

Dynamic modulus of elasticity (MoE_{dyn})

This should be estimated almost certainly from time of flight measurements which should be taken over as long a length of the beam as is possible. The measured in situ density (adjusted for moisture content) should be used in calculating MoE_{dyn}. Several measurements should be taken and judgement used to determine the value of MoE_{dyn}.

In situ moisture content

Electrical resistance or capacitance type moisture meters are quick, cheap and reliable and so can be used for this purpose. Measure moisture content at a minimum of five points along the length (L) of a beam (at 0L, 0.25L, 0.5L, 0.75L and 1L from one support) and then average readings to obtain the in situ moisture content of the beam. Engineering judgement must be used in cases of significantly varying moisture content and excessive moisture content.

Knot measure

Identify the zone of the beam where significant deflections or bending moments will arise (this is a matter for a structural engineer on site) and within this zone, choose the worst 300mm and 400mm lengths. Knots can be measured using a steel tape measure or a steel ruler marked in mm increments. It may be found useful to mark out the zone of interest directly onto the beam and to reference each face of the beam.

Knot cluster measurement, over the 300mm length, and over all four longitudinal faces of the beam: measure the transverse diameter of each knot separately (accounting for overlapping knots). The knot ratio kc3 is obtained by dividing the sum of the knot cluster by the length of the perimeter of the beam and this ratio kc3 can be used in the estimation of MoR.

Knot group measurement, over the 400mm length, and over all four longitudinal faces of the beam: measure the transverse diameter of each knot separately. The knot ratio kg3 is obtained by dividing the sum of the knot group (with no accounting for overlapping knots) by the length of the perimeter of the beam and this ratio kg3 can be used in the estimation of MoE.

If it is not possible to gain access to all four longitudinal faces of the beam, then measure as many faces as possible to obtain pro-rata variants on the ratios described above for knot clusters (for example kc8 to kc11) and knot groups (for example kg9 to kg12), as described in Chapter 5.

In situ density

The predictive models are based on the SDT approach of taking micro cores which is straightforward and gives robust results but causes more damage to the beam than using the drill chip extraction method (DCE), which is therefore, potentially a better alternative. Test results should ideally be obtained at a minimum of two locations along the length of the beam. A practical arrangement for three cores, could be for two horizontal cores located at say 0.3 span from supports and a single vertical core located at say 0.2 span from one support. This provides density measurements at a minimum of three locations which should be averaged for use in estimation of characteristic density and for improving the accuracy of acoustic resonance or time of flight testing and subsequent conversion to MoE_{dyn}.

It may be that, due to access issues, only horizontal drilling or only vertical drilling is possible, or drilling is only possible at one location. In these circumstances, the best measurements available should be taken and used. Density values measured on site should be adjusted to account for moisture content using Equation (3) from EN384.

Slope of grain (SoG)

This may be estimated from splits and fissures present in the longitudinal faces of the beam or using a swivel handled scribe, as described in EN1309-3 (CEN, 2018a). Ideally, measurement of longitudinal deviation of grain should be taken on two perpendicular faces and combined to give a three dimensional (3D) slope of grain (SoG). This measurement should be of the general slope of grain in the timber beam (and not the local deviation of grain around knots etc.). If it is not possible to access two perpendicular faces, then a 2D SoG should be measured and used in predictive models. As noted above, the best measurements available should be taken and an appropriate model can be used to accommodate any shortcomings.

8.5.2 Estimate lower confidence limits

On occasion, it may not be possible to measure on site all of the predictor variables, or to measure them in the best possible way. Typical examples of this are described below:

- Knots – it may not be possible to gain access to all four faces of a joist and so a knot measure based on fewer faces must suffice
- NDT for MoE_{dyn} – an inspecting engineer may not have the necessary equipment
- Density – it may not be possible to obtain two perpendicular cores and so the estimation of density must be based on a single core or two parallel cores
- SoG – it may only be possible to measure the 2D SoG in place of 3D SoG

A selection of models is presented in Table 8.3 and Table 8.4 to illustrate models which allow for several variants of site investigation results. This selection can be expanded, as the data set for the predictive models expands, to cover the most common eventualities. The star ratings of the models are differentiated by the range of their predictions (before adjustment) and are placed alongside the recommended version of the model in question.

Structural engineers are encouraged to make use of the three and four star models as these have the greatest predictive powers and will determine the most accurate values of properties. Models with one and two stars are not recommended for use in practice, however, the two star models may be potentially developed in the future with improved data and adjustment. Finally, models with multiple predictor variables are always preferred to ones with single predictors.

Although there are multiple models for MoE_{LCL} and MoR_{LCL} , only one model is described for ρ_{LCL} and this is presented below

$$Density_{LCL} = 158 + 0.53 \times Averaged\ micro\ clear\ density \qquad (8.26)$$

Table 8.3. Predictive models for MoE_{LCL} with star ratings

Multiple predictor 'Best' model (unadjusted)	Range	Min	Max	Rating
$MoE_{LCL} = 0.947 + 0.820\,MoEdyn - 1.072\,kg3 - 0.040\,SoG$	10.8	3.2	14.1	✱✱✱✱
Multiple predictor models (unadjusted)				
$MoE_{LCL} = 0.6132 + 0.8753\,MoEdyn - 0.001595\,density$	10.7	3.5	14.2	✱✱✱✱
$MoE_{LCL} = -0.335 - 4.234\,kg3 + 0.025\,density$	9.1	4.7	13.8	
$MoE_{LCL} = 11.0034 - 5.5444\,kg3 - 0.1121\,SoG$	6.8	3.9	10.8	
Multiple predictor models (adjusted)				
$Adjusted\ MoE_{LCL} = -3.2734 - 4.2353\,kg3 + 0.03008\,density$	8.6	3.2	10.5	✱✱✱
$Adjusted\ MoE_{LCL} = 11.0035 - 6.2493\,kg3 - 0.1121\,SoG$	7.7	3.2	11.0	✱✱
Single predictor models (unadjusted)				
$MoE_{LCL} = 0.1425 + 0.8517\,MoE_{dyn}$	10.5	3.5	14.1	
$MoE_{LCL} = -2.3374 + 0.0258\ \mathrm{density}$	7.2	5.4	12.6	
$MoE_{LCL} = 9.7545 - 4.2688\,kg10$	6.1	3.7	9.8	
$MoE_{LCL} = 9.7960 - 4.6282\,kg3$	5.3	4.5	9.8	
$MoE_{LCL} = 8.5956 - 0.1021\ \mathrm{SoG}$	1.9	6.6	8.5	
Single predictor models (adjusted)				
$Adjusted\ MoE_{LCL} = -0.2512 + 0.8758\,MoEdyn$	10.8	3.2	14.1	✱✱✱✱
$Adjusted\ MoE_{LCL} = -6.8456 + 0.0336\ \mathrm{density}$	9.3	3.2	12.6	✱✱✱
$Adjusted\ MoE_{LCL} = 9.7545 - 4.5596\,kg10$	6.5	3.2	9.8	✱✱
$Adjusted\ MoE_{LCL} = 9.7960 - 5.7488\,kg3$	6.5	3.2	9.8	✱✱
$Adjusted\ MoE_{LCL} = 8.8467 - 0.2796\ \mathrm{SoG}$	5.2	3.2	8.5	✱

Table 8.4. Predictive models for MoR_{LCL} with star ratings

Multiple predictor models ('Best' model unadjusted)	Range	Min	Max	Rating
$MoR_{LCL} = 8.07 + 1.78\ MoEdyn - 14.25\ kc3$	26.89	8.1	35.0	✱✱✱✱
Multiple predictor model (unadjusted)				
$MoR_{LCL} = 5.689 + 0.05056\ Dens - 19.8069\ kc3$	23.45	10.0	33.5	
Multiple predictor model (adjusted)				
$Adjusted\ MoR_{LCL} = 1.707 + 0.05745\ Dens - 19.80\ kc3$	25.04	8.4	34.9	✱✱✱✱
Single predictor models (unadjusted)				
$MoR_{LCL} = 3.725 + 1.7487\ MoE_{dyn}$	21.6	10.7	32.3	
$MoR_{LCL} = 0.996 + 0.0435\ density$	12.1	14.1	26.2	
$MoR_{LCL} = 23.54 - 18.7764\ kc3$	14.3	9.2	23.5	
$MoR_{LCL} = 21.220 - 12.3365\ kc9$	10.7	10.6	21.2	
$MoR_{LCL} = 17.085 - 0.2370\ SoG$	4.4	12.3	16.7	
Single predictor models (adjusted)				
$Adjusted\ MoR_{LCL} = 0.258 + 1.961\ MoE_{dyn}$	24.2	8.1	32.3	✱✱✱
$Adjusted\ MoR_{LCL} = -11.451 + 0.065\ density$	18.1	8.1	26.2	✱✱
$Adjusted\ MoR_{LCL} = 23.54 - 20.258\ kc3$	15.4	8.1	23.5	✱✱
$Adjusted\ MoR_{LCL} = 21.22 - 15.195\ kc9$	13.1	8.1	21.2	✱✱
$Adjusted\ MoR_{LCL} = 17.408 - 0.465\ SoG$	8.7	8.1	16.7	✱

In Table 8.3 and Table 8.4, no variants of the site measurements of SoG or density are presented. The effect of the inferior measures of density (just one reading in place of two or three) and SoG (2D in place of 3D) have not yet been fully investigated but are not expected to significantly affect the models for MoE and MoR due to their small effects. It would be useful to investigate the effects of 2D and 3D SoG and particularly the modelling of density based on single cores or single DCE readings in place of two or three, as this is the primary predictor for density, which in turn is required for the calculation of MoE_{dyn}. So, two more aspects of model building merit further research.

The MoR value from the predictive model requires no adjustment for moisture content but requires the application of the height adjustment factor k_h from EN384 to determine MoR_{LCL} .

The MoE_{dyn} value used in the predictive model for MoE is already adjusted for moisture content and additionally, the predictive model is based on shear free MoE results and so already includes any necessary adjustments for shear.

The density value from the predictive model requires adjustment for moisture content in accordance with EN384 to determine ρ_{LCL} .

The output of the predictive models are the estimates of the lower 50% two sided confidence limits around the mean MoE and the 0.05 quantiles of MoR and density which are termed MoE_{LCL} , MoR_{LCL} and ρ_{LCL} . These are used as the basis to determine the key characteristic values.

8.5.3 Determine characteristic values

Each of the outputs of the predictive models require further adjustment for sample selection (see Sub-section 7.2.3), prior grading (see Section 7.10) and mechanical damage (see Sub-section 2.5.5 and Section 7.6) using factors F1, F2 and F3, which are presented in Table 8.5.

The density value from the predictive model, ρ_{LCL} requires further adjustment to determine the characteristic value of density ρ_k

$$\rho_k = \rho_{LCL} \times F1 \times F2 \tag{8.27}$$

The modulus of elasticity value from the predictive model MoE_{LCL} requires further adjustment to determine the characteristic value of MoE, $E_{m,0,mean}$

$$E_{m,0,mean} = MoE_{LCL} \times F1 \times F2 \times F3 \tag{8.28}$$

The bending strength value from the predictive model MoR_{LCL} requires further adjustment to determine the characteristic value of $f_{m.k}$

$$f_{m,k} = MoR_{LCL} \times F1 \times F2 \times F3 \tag{8.29}$$

Table 8.5. Factors to adjust model estimates for characteristic values

	MoR	MoE	Density		Notes
F1	✓			0.8	Sample selection
		✓	✓	0.9	Sample selection
F2	✓	✓	✓	1	Prior grading – desk study neutral or indicates likely removal of poor quality timber
				0.95	Prior grading – desk study indicates likely removal of better quality timber
F3	✓	✓		1	Mechanical damage – inspection shows moderate past usage and moderate mechanical damage
				0.9	Mechanical damage – inspection shows very heavy past usage or exceptional mechanical damage due to small fixings, e.g. nails and nail holes

No factors are recommended for wane, fissures, insect and fungal attack. It is assumed that the timber to which the characteristic values apply is sound and free from any significant effects of insect or fungal attack. It is considered that an engineer should investigate and measure any reduced cross sectional area or bearing area, etc. and take account accordingly in any structural analysis and design calculations.

8.6 Conclusions

In this chapter, an extended process of model building was followed to create a range of predictive models for the 50% two sided lower confidence limit values of MoE, density and MoR, based on the statistical methods used in the Eurocodes. These values are adjusted to determine characteristic values which can be used in structural calculations carried out in accordance with the Eurocodes. The models are based on a relatively small sample of only four species and must be developed using a more representative sample of the population in the future. Unique contributions to knowledge are:

(i) The application of statistical techniques such as quantile regression and bootstrapping (to find the confidence intervals around quantiles) to timber data in novel ways

(ii) The development of the methodology for the creation of the new predictive models

For MoE and MoR, several models are created to illustrate the use of different combinations of predictor variables, ranging from 'best' models through other multivariate models to single predictor models. Due to the nature of regression and the varying strengths and weaknesses of the predictor variables, it is necessary to penalise some models to ensure conservative outcomes.

It is shown that visual grading and strength classification perform poorly with regard to the determination of characteristic values of individual joists (as the visual grading results differentiate weakly between timber joists of differing strengths, stiffnesses and densities) whereas the new predictive models are shown to perform well.

Chapter 9 Discussion and conclusions

9.1 Introduction

In this final chapter, the original goals of the research are reviewed and then, the outcomes of the research are considered which cover the primary output of the thesis, the benefits of the models developed and their validation and verification. Next, the implications of the work are discussed in relation to structural engineering and the timber industry. Finally, in this nascent field of research, there is a great deal of further work that can usefully be done and this is organised into three fields: philosophy of models, contexts of models and timber research. The chapter ends with some brief concluding remarks.

9.2 Goals of the research

9.2.1 Aim of the research

The aim, to create new preliminary models for the prediction of the mechanical and physical properties of individual timber elements using a combination of visual and non-destructive and semi-destructive techniques is achieved. Reference should be made to the tables of preliminary models presented in Chapter 8.

9.2.2 Objectives of the research

Each of the objectives of the research described in Chapter 1 have been addressed:

Obj.1. An extensive literature review is presented in Chapter 2, along with additional, smaller, more focussed literature reviews in Chapters 4 and 6.

Obj.2. A data set was assembled of four minor species (n=527), as is described in Chapter 3. The sample was investigated by NDT, SDT and visual inspection before being tested to destruction to create an extensive data set. The results of the testing are presented in Chapters 4 and 5.

Obj.3. The statistical background to the Eurocodes was investigated and is described in both Chapter 3 and in the published document linked in the appendices: Guide to statistics in the Eurocodes for timber engineers.

Obj.4. In Chapter 5, the test data is processed and the most appropriate measurements are determined. Next, in Chapter 8, new statistical models to predict estimates (and their lower bound confidence limits) of the mechanical and physical properties of timber elements are developed. Appendices D, E and F provide further information on the model building processes.

Obj.5. The contexts of the application of the models are considered in Chapter 7, where methods are described to determine in situ timber's characteristic material properties in accordance with the Eurocodes.

Obj.6. In order to assess the performance of the predictive models, a second, smaller data set of Sitka spruce (n=60) was obtained and processed and the lower confidence limits of mean MoE and the 0.05 quantile of MoR were determined and compared with measured values and the results of visual grading followed by strength classification. The positive results of this assessment are presented in Chapter 8.

9.2.3 Validity and verification

The validity of the work is derived from its coherence, linking (i) the working practices of structural engineers carrying out structural appraisals, (ii) the consideration of the contexts of timber elements in existing structures (such as their age or status) and (iii) the structural Eurocodes.

A successful beginning has been made in verifying MoE_{LCL} and MoR_{LCL} predicted values using the Sitka spruce data set (n=60) and the results are promising. More work is still needed which will involve the extension of the original data set with more samples which together will be increasingly representative of the population of in situ structural timber in the UK. Thus, as the basis of the predictive models improves, so too will the predictive models.

9.3 Outcomes of the research

9.3.1 Primary output of the thesis

For strong economic, environmental and social reasons, we must reuse in situ structural timber and to do this, we must be able to find its mechanical and physical properties accurately and at an appropriate level of detail. Current methods based on visual grading codes are shown in this thesis to be inaccurate, imprecise and inappropriate. Similarly, methods based on the assumption that knots act as voids are shown to be ineffectual.

The primary output of this thesis is the development of preliminary predictive models for individual in situ structural timber elements for the characteristic values of MoE, MoR and density. The models are based on a limited sample of four minor species grown in the UK (n=527) and have successfully been applied to a fresh data set of another UK grown species (Sitka spruce, n=60) with promising results.

The manner in which the data set for the predictive models needs to be extended is discussed and outlined, together with new methodologies for accounting for issues such as selection bias, prior grading and the deterioration of structural timber in service.

9.3.2 Benefits of the models

The models developed have a number of benefits. Firstly, they do not ‘reject’ joists that lie outside tabulated limits of features associated with visual grades and so the mechanical and physical properties of all joists can be determined. Given that, for instance, BS4978 rejected around one third of the joists from the sample of four minor species, this is a significant benefit. Secondly, the range of models is flexible and allows practitioners to take one or all measurements of a range of features of an in situ timber element and still be able to derive estimates of its properties.

Thirdly, the outputs of the models are graded for each property under consideration and not forced into a small number of strength classes. This improved precision enables structural engineers to make the most of the strength or stiffness of timber elements. Fourthly, the models are derived in accordance with the Eurocodes and complement their design approach. In this way, their outcomes can be used directly by structural engineers in design calculations.

Finally, it is considered that this approach to modelling, based on the UK, is transferable to other countries and could be refined to focus on the particular species and growth areas etc. that pertain.

9.3.3 Unique contributions to knowledge

There are several unique contributions to knowledge arising from the work:

(i) The most important of the contributions to knowledge is the development of a philosophy for the building of predictive models. The Eurocodes' characteristic values of the material properties of timber are based on the lower confidence limits of statistics which in turn are based on the distribution of large samples and so it was necessary to develop models for an individual timber element, based on a single or a few combined measurements of predictor variables.

(ii) Research into the predictive powers of currently used knot measures and ratios led to the development of new knot measures and ratios with superior predictive powers in comparison to currently used measures and ratios.

(iii) The statistical techniques of quantile regression and bootstrapping (to find the confidence intervals around quantiles) were applied to timber data in novel ways in the creation of the predictive models for the 5th percentiles of MoR and density.

(iv) The research considered and accounted for significant factors such as selection bias and potential prior grading and the deterioration of wood during its life in service in relation to the predictive models. The application of observational statistical techniques from the fields of social science and economics to timber research is new.

(v) The limitations of the outcomes of this study (which is based on a sample of new UK grown structural sized timber joists) are presented and recommendations are outlined to address them in the future. These recommendations represent new approaches in the field of research into in situ timber.

In addition to point (ii) above, the use of paired micro cores for the estimation of density provides a robust estimate and does not appear to have been used before (although taking small samples to estimate the properties of the larger test piece is not really a new idea).

In addition to point (iv) above, the research in the thesis into the preliminary mapping of the supply of structural timber to the UK since the 17^{th} century, provides a necessary starting point in understanding the variability of in situ structural timber in the UK and has not been done before.

9.4 Implications of the work

9.4.1 Structural engineering

Despite much authoritative advice to the contrary, structural engineers should stop using visual grading codes to assess in situ timber elements. This current practice is shown in the thesis to be inappropriate and ineffective. A lack of understanding of timber by structural engineers is apparent and should be addressed by CPD and more teaching of timber in civil engineering degree programmes.

In order to make good use of the characteristic values of timber properties from the predictive models, the current levels of load factors and materials factors required by the Eurocodes for the design of new structures must be recalibrated for the design for existing structures. Due to the reduced variance in predicted properties, a recommendation for the reduction in the partial factor for material properties γ_M for machine graded timber has already been made by others (Stapel, Van De Kuilen and Kuilen, 2013) and is here made for the outcomes of the predictive models. The current levels of the factors are too high and work against the economic, environmental and social rationale for refurbishment.

The regression models in this thesis follow the statistical requirements of the Eurocodes (based on distribution models) to ensure that their outputs are compatible for design. However, the residual errors of regression models are much smaller than those in distribution models and so the use of 50% two sided lower confidence limits have a much smaller effect for the former compared to the latter. Consideration should therefore be given to finding a different way to account for error in regression models that still accords with the Eurocodes.

9.4.2 Timber industry

There is a potential for using quantile regression in place of OLS regression in machine grading of new timber and this is worth exploring. The development of predictive models for individual timber elements described in this thesis can also be applied (with some adaptations) to salvaged timber and even to new timber. For challenging projects, this would allow the sorting of timber on site or in the woodyard, and could allow the timber resource to be used more efficiently than it currently is.

9.5 Further work

9.5.1 Philosophy of models

The key issue requiring further work is the development of the sample selection model to account for the selection bias discussed in Chapter 7. More data will make this task easier but due to the observational basis of the predictive models, it will always require an understanding of contexts and the application of judgement.

The predictive models developed in this study exclude species or species groups, growth areas and eras of construction. Now that the first species free predictive models have been developed, the inclusion of these refinements into new predictive models could be considered, especially, once the extent of the data set, upon which model building is based is increased.

In this thesis there is some discussion of the choice of straight versus curved line estimates and lower confidence limits. The argument for straight lines is only marginally stronger than the argument for curved ones and as the contexts of research change and more data becomes available, this decision must be revisited, balancing accuracy, compliance with the Eurocodes and complexity.

Again the methods used to adjust the predictive models for MoE_{LCL} and MoR_{LCL}, based on the weaker variables, should also be revisited as more data becomes available. As the adjustment of models is developed, so too, the star rating system must be reviewed and developed. Future decisions will need to consider how the predictive models are made available to structural engineers and who should take responsibility for applying judgement to ensure that estimates are conservative.

9.5.2 Contexts of models

There is much UK based historical research that can usefully provide contexts for the predictive models and that could be broken down by decade and by region or city. This includes: (i) timber supply and use (considering species, quality and growth areas), (ii) the extent of appearance grading of timber and the methods used for it, (iii) the relationship between what timber was specified and what timber was used in structures, (iv) evidence of practices that led to the effect of prior grading; broadly, any furtherance of our knowledge of the timber elements that are to be found in the structures around the UK.

9.5.3 Timber research

The single most important piece of further work that can be done is to create and implement a protocol for the testing and reporting and collating of data on existing timber and to develop an extended data set as the best way to deal with the important issue of selection bias. The initial extension of the data set could focus on the most common species, from the most common eras of construction, from the most common growth areas etc. (e.g. Norway spruce and Scots pine are the most commonly used European timbers and so should be included as a priority).

Additionally, valuable research can also be carried out in smaller packages into aspects that arose during the development of the predictive models.

Research into the effects of various factors on the properties of timber: (i) nail damage, which is occasionally apparent in existing timber, (ii) splits and shakes, which are more prevalent in old timber than in new, and (iii) temperature cycling of timber (e.g. found in hot/cold roofs), which anecdotally appears to lead to weakening and brittleness of timber. In future, the predictive model could be extended beyond the current set of predictor variables to include features such as fissures, warp, wane, soft rot and dote and insect damage.

Research into relationships: (i) between the primary and secondary properties of old timber to confirm that these hold true in the same way as they do for new timber, and (ii) between MoE_{dyn} and MoE and MoR to confirm that their relationships for new timber holds true for old timber in the same way (also, for different species, different degrees of fungal or insect attack, previous load cycling or overloading, etc.).

Research into the measurements used in the predictive models: (i) the use of single radial or tangential micro cores in place of pairs of cores for the estimation of density, and (ii) the rationalisation of the knot parameters kc3 and kg3 over 300mm or 400mm or some other length.

Finally, to help in the development of the sample selection model, research into: (i) the presence and the statistical effects of prior grading of timber elements in existing structures (possibly using notional data sets based on physical research), and (ii) the quantification of the changes in timber properties over decades and centuries (including the expected increase in variance).

9.6 Concluding remarks

This wide ranging exploratory study considered many aspects in the appraisal of individual in situ timber elements in an attempt to develop a comprehensive methodology. This led to much time being spent investigating approaches which finally were not used (such as the use of visual grading codes of practice for in situ timber or the treatment of knots as voids) and statistical techniques which also were not used (such as prediction and tolerance intervals and a range of adjustments for weak regression models). An attempt has been made to link the laboratory testing and contextual and historical research of this study with (i) the results of previous timber research, (ii) a practical approach to the appraisal of structures by practising structural engineers and (iii) the structural Eurocodes. Altogether, this has led to a very long thesis.

It has resulted in new ways of applying statistical approaches to the outcomes of NDT, SDT and visual inspection to create a range of preliminary predictive models to estimate the key characteristic mechanical and physical properties of individual timber elements in accordance with the Eurocodes.

The most useful outcomes of the study are (i) the development of a methodology for the creation of predictive models and (ii) the development of preliminary predictive models and (iii) an outline of what further work is required in the future to extend the basis of the preliminary predictive models in order to create models for use by practising structural engineers.

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Appendix A Discussion of ordinary least squares (OLS) regression

A.1 Basis of OLS regression

OLS regression can be used to create models linking measurable parameters with the mechanical and physical properties of timber elements. This does not require that there is a deterministic relationship between the predictors and the properties, simply a statistical one.

There are four conditions for linear regression which must be met to confirm the appropriateness of the analysis are:

The mean response of the predicted variable $\hat{y}_i$ is a linear function of the predictor value x_i

The errors ε_i are independent

The errors ε_i at each predictor value x_i are normally distributed

The errors ε_i at each predictor value x_i have equal variances

In short, a linear model is appropriate and its errors are independent normal random variables which in turn is also summarised as "iid" (independent and identically distributed) and as the absence of heteroscedasticity.

Firstly, the assumption of linearity in the prediction of mechanical and physical properties of timber is common. Secondly, as many tests and intervals are to some degree sensitive to departures from independence, normality and equal variance, all three of the remaining assumptions need commenting upon for almost any statistical analysis of timber data. In particular, it should be noted that as prediction intervals based on OLS are sensitive to departures from normality, that this is another positive reason for the adoption of quantile regression over OLS regression as a model for the prediction of MoR and density.

For the prediction of MoE, using OLS regression, the four conditions noted above can be assessed using the statistical software R. For the prediction of MoR and density using quantile regression, the non-parametric modelling is less susceptible to deviations from the four conditions. Nevertheless, these should still be considered. Bearing in mind these conditions, this is a strong argument to develop a model for the prediction of MoE based on the median (rather than the mean) and so reduce the risk associated with encountering samples of timber that do not satisfy the four conditions.

Finding the mean of a conditional distribution (A.1)

Returning to the OLS analysis, for a sample, the equation for simple linear regression (the least squares regression line) is

$$\hat{y}_i = b_0 + b_1 x_i \tag{A.1}$$

$\hat{y}_i$ is the predicted response variable

b_0 is the intercept of the linear regression line on the y axis

b_1 is the slope of the linear regression line

x_i is the predictor value

The prediction error or residual error, for an individual data point, is

$$e_i = y_i - \hat{y}_i \tag{A.2}$$

e_i is the residual error for data point y_i

y_i is the actual measured response variable based on a measured predictor value

The slope and intercept of the OLS regression equation are determined as follows. The slightly complicated equation for b_1 is to account for both positive and negative values of $(x_i - \bar{x})$ and $(y_i - y)$:

$$b_1 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})\ (y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{A.3}$$

$$b_0 = \bar{y} - b_1\, \bar{x}$$

$\bar{y}$ is the mean value of the response variable

$\bar{x}$ is the mean value of the predictor variable

A.2 Understanding the fit of an OLS regression model

In order to understand the fit of the regression line to the data, it is necessary to define several terms ($SST,\ s^2,\ s,\ SSE,\ MSE,\ SSR,\ r^2,\ r$). These definitions are followed by a brief discussion of the coefficient of determination, r^2.

The total sum of squares (SST) quantifies how the data points vary around their mean and is the numerator of the sample variance

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{A.4}$$

The sample variance solely relates to the predicted response variable and is denoted s^2 and is an estimate of the variance σ^2 of a single population. The greater the sum of the differences between individual data points and the mean, then the greater is the variance. Once again, the squared term accounts for negative values (as is the case in several of the following equations)

$$s^2 = \frac{SST}{n-1} = \frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n-1} \tag{A.5}$$

The standard deviation of the sample, s is the square root of the variance

$$s = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n-1}} \tag{A.6}$$

The sum of squared errors (SSE) quantifies how the data points vary around the regression line

$$SSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{A.7}$$

The mean square error (MSE) estimates the variance σ^2 of the many subpopulations based on each of the predictor variables x_i used in creating the linear regression equation

$$MSE = \frac{SSE}{n-2} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-2} \tag{A.8}$$

The residual standard error (S) is also known as the regression standard error or just the standard error (SE) and is the estimated standard deviation of the errors

$$S = \sqrt{MSE} \tag{A.9}$$

The residual sum of squares or the sum of squared residuals (SSR) quantifies the difference between the SST (based upon the mean) and the SSE (based upon the linear regression model) and this gives an indication of the strength of the predictive model.

$$SSR = SST - SSE = \sum_{i=1}^{n}(y_i - \bar{y})^2 - \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{A.10}$$

$$SSR = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 \tag{A.11}$$

The coefficient of determination (also known as r^2) gives an indication of the fit of the regression line with the data and is the ratio of the SSR and the SST.

$$r^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{A.12}$$

The coefficient of determination r^2 is said to 'explain' the extent of variation of the response variable (about its mean) by the predictor variable. How much can the variation in the response variable about its mean be reduced by accounting for the predictor variable? This assumes an association between the variables which may or may not be causal.

As the basis of OLS regression is the minimisation of the sum of the squared error, outliers (with large errors and much larger squared errors) have a disproportionate effect on the model. The effect of outliers is reduced by adopting a least absolute errors method such as the method used in quantile regression.

A.3 Confidence interval around the slope of an OLS regression model

The linear equation based on a sample of data (and discussed above) is used to estimate the linear equation for the entire population

$$\hat{y}_i = \beta_0 + \beta_1 x_i \tag{A.13}$$

The two linear equations will differ, and it is possible to determine the probability of the sample linear equation slope lying within the confidence interval of the population linear equation slope. By doing this, it is possible to confirm whether or not there is a linear relationship between the predictor and respondent variables.

The mean square error is defined above and the confidence interval for β_1 can be expressed in words as

$$'sample\ estimate\ \pm\ t - mulitiplier\ \times\ standard\ error'$$

$$b_1 \pm t_{(\alpha/_2,\ n-2)} \times \left(\frac{\sqrt{MSE}}{\sqrt{\sum(x_i - \bar{x})^2}}\right) \tag{A.14}$$

This confidence interval gives the limits of values for β_1 and if it contains zero, then it is concluded that there is not a linear relationship between the predictor and response variables in the population. The test statistic t^* is calculated from the following formula:

$$t^* = \frac{b_1 - \beta_1}{\left(\frac{\sqrt{MSE}}{\sqrt{\sum(x_i - \bar{x})^2}}\right)} \tag{A.15}$$

By setting β_1 as zero, the above equation gives the t-multiplier and hence, the test statistic. From the test statistic, the probability can be calculated.

It is seen that the width of the confidence interval is strongly influenced by the sample size, reducing as sample size increases. Firstly, the term $t_{(\alpha/_2, n-2)}$ reduces as the sample size increases, thus reducing the t-multiplier and the width of the confidence interval. Secondly, the MSE term reduces in a linear fashion as sample size increases, thus reducing the second term of the equation and the width of the confidence interval. Thirdly, the term $\sqrt{\sum(x_i - \bar{x})^2}$ which is determined by the spread of the predictor values x_i from their average $\bar{x}$, will also increase as the sample size increases, again reducing the second term of the equation and the width of the confidence interval.

A.4 Confidence interval around the mean of an OLS regression model

When considering the estimation of a population parameter such as the mean response in the population for a predictor variable of x_i , this is based on the typical formula for a confidence interval, with $\hat{y}_i$ as the predicted value of the dependent variable and can be expressed in words as

$$'sample\ estimate\ \pm\ t - mulitiplier\ \times\ standard\ error'$$

$$\hat{y}_i \pm\ t_{(\alpha/_2,\ n-2)}\ \times\ \sqrt{MSE\ \times \left(\frac{1}{n} + \frac{(x_i -\ \bar{x})^2}{\sum(x_i -\ \bar{x})^2}\right)} \qquad \text{(A.16)}$$

The final term (the square rooted term) is also known as the 'standard error of the fit' and this term accounts for the variation due to estimating the mean of the population μ_Y for a given predictor variable x_i . It is again seen that the width of the confidence interval is strongly influenced by the sample size and the spread of the predictor values x_i from their average $\bar{x}$. Larger sample sizes and larger spreads of predictor values reduce the confidence interval.

This confidence interval applies to any predictor x_i lying within the spread of data of the sample in the study and the typical conditions for linear regression outlined earlier also apply.

A.5 Multiple linear regression

Multiple linear regression can be used to predict a single dependent variable from more than one predictor variable. The assumptions for OLS regression remain a requirement for multiple linear regression, which is also based on a least squares approach. The multiple linear regression model equation will take a form similar to the OLS regression one

$$\hat{y}_i =\ b_0 +\ b_1\, x_1 +\ b_2\, x_2 +\ b_3\, x_3 +\ b_4\, x_4 \qquad \text{(A.17)}$$

The interpretation of this equation is similar to the simple OLS regression equation; if all predictor variables are held constant apart from say, x_1 , and this is increased by unity, then $\hat{y}_i$ increases by b_1 . So, the size of b_i is an indication of the importance of its associated predictor variable.

One added complication of multiple linear regression, when compared to OLS regression is the need to choose which predictor variables are to be included in the model. This process can be dealt with by methods such as all subsets regression and an examination of the relationships and interactions between each of the variables.

A balance must be struck between (i) exercising too much caution when considering multiple predictor variables to avoid over-fitting data and finding correlations by chance that only fit this particular data set and (ii) including sufficient predictor variables to create a model (or series of models) that can be most useful to an engineer carrying out an assessment on site.

Appendix B Discussion of quantiles and quantile regression

B.1 Finding the quantile of a sample

Quantiles and percentiles are effectively the same but make use of different notation. The 5th percentile is the same as the 0.05 quantile. So, determining a quantile of a sample is a relatively straightforward exercise dealt with in elementary textbooks on statistics. The 0.05 quantile is used to determine the characteristic value of both bending strength and density of a population of timber, based on the test results of a sample of that population. For a given sample of observations, the quantile can be determined parametrically or non-parametrically. In grading timber, the parametric method assumes a lognormal distribution (CEN, 2016a).

The non-parametric calculation of quantiles of a sample requires data to be ranked from 1 to n in order of increasing size and the kth percentile can be obtained in more than one way, for instance

$$q = k(n+1)/100 \tag{B.1}$$

q is the value of the kth percentile of n data points. Where q is not a whole number, interpolation is needed between the two adjacent values (Altman and Bland, 1994).

A variant of this approach is used in the grading of timber in Europe (CEN, 2016a) whereby the number n is not increased by one but simply used on its own

$$p = \frac{i}{n}$$

p is the percentile of value f_p linearly interpreted from adjacent values; n is the sample size; i is the i th data point ranked in ascending order.

These approaches are appropriate to finding the quantile of a sample. In a section below, the approaches to finding the quantile of a conditional distribution are discussed.

B.2 Confidence interval around a quantile of a sample

This follows a similar approach to the confidence interval around the mean of a sample, as both approaches are dealing with a population parameter.

In the Eurocodes, the lower confidence limit, LCL, is determined at a confidence level of $\alpha = 75\%$, and the formula for this can be written, first in words

$$'sample\ mean\ value - (t - mulitiplier) \times standard\ error\ of\ the\ mean\ (SEM)'$$

$$LCL = \bar{y} - t_{(1-{}^{\alpha}/_{2}\,;\,n-1\,;\,\delta)} \times \frac{s_y}{\sqrt{n}} \tag{B.2}$$

$$LCL = \bar{y} - t_{(1-\alpha/_2\,;\,n-1\,;\,\delta)} \times \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n-1}}}{\sqrt{n}} \tag{B.3}$$

$t_{(1-\alpha/_2\,;\,n-1\,;\,\delta)}$ is the $\left(1 - \alpha/_2\right)$ quantile of a noncentral t-distribution with $n-1$ degrees of freedom and noncentrality parameter δ

$\phi_{norm}\,(Z)$ is the standard normal cumulative distribution function (cdf) giving $Pr(Z\ \le z)$

Z is a random variable with a normal distribution, mean $\mu = 0$ and standard deviation $\sigma = 1$

$z_{(p)} = \phi_{norm}^{-1}\,(p)$ is the p percentile (or quantile) of the standard normal distribution

$$\delta = -\sqrt{n} \times z_p = \sqrt{n} \times z_{(1-p)} \tag{B.4}$$

The computer programme R can be used to find many of these parameters (using functions such as: pnorm(), qnorm(), qt()). Reference should also be made to EN14358 which makes use of this approach in determining characteristic values of density.

Due to the non-symmetrical nature of the probability distribution around the quantile, the upper and lower limits are calculated to be at different distances from the quantile, with the lower confidence limit being located further from the 0.05 quantile than the upper.

B.3 Introduction to quantile regression

Despite the calculation of a quantile of a sample being straightforward and well documented, determining the quantile of a conditional distribution in a non-parametric manner, is a relatively recent development which, at the time of writing, was not found to have been used in the statistical analysis of the mechanical and physical properties of timber elements.

Although the basic principles of quantile regression were described many years ago, it was not until the latter part of the twentieth century, with the advent of computing power, that it became a viable statistical tool. It provides a method to investigate relationships between variables from all parts of a conditional distribution (not just focussing on the mean, but also focussing on any part of the distribution, including the tails) (Koenker and Bassett, 1978). It was successfully developed as a statistical package for computer software (Koenker, 2019); programmes such as R and SPSS include packages for quantile regression.

The OLS linear regression model focusses on the conditional mean of the independent variable and gives relatively little information about the remainder of its distribution. Whereas, with quantile regression, a range of conditional quantiles can be used to describe the entire distribution of an independent variable.

To derive the quantile of a conditional distribution, a linear model could be developed based on the parametric approach of ordinary least squares (OLS) regression. Quantiles could then be determined based on the mean, the standard deviation and the distribution of the dependent variable. Reference should be made to the earlier discussion of OLS approach and its assumptions. There, it is concluded that the disadvantages of OLS regression (particularly with regard to outliers and heteroscedasticity) are sufficient to merit consideration of alternative approaches.

A brief explanation of the method of quantile regression is given in the next section and here, is a summary of its pros and cons.

B.4 Basis of quantile regression

The basic quantile regression equation differs slightly from the OLS regression equation in that the β term (i.e. the slope coefficient) is qualified by the subscript q which indicates which particular quantile the slope coefficient refers to. The error in both models (e_i) is still minimised, but again, in slightly different ways. Here is the basic quantile regression equation:

$$y_i = x_i'\beta_q + e_i \tag{B.5}$$

y_i is the dependent variable; x_i' is the predictor variable (or a series of predictor variables) and e_i is the error term of the model.

In quantile regression, the error term is derived slightly differently from in OLS regression. In OLS regression, the sum of the squares of the prediction error $\sum_i e_i^2$ is minimised. Whereas in quantile regression, asymmetric penalties are given for under-prediction and over-prediction and these are combined with the absolute values of the error term such that for a given quantile the combined values are minimised (Katchova, 2013). This is described in the equation below

$$Q(\beta_q) = \sum_i q\,|e_i| + \sum_i (1-q)\,|e_i| \tag{B.6}$$

For the median (0.5 quantile), both of the right hand terms reduce to $\sum_i 0.5\,|e_i|$, leading to the entire right hand term reducing to $\sum_i |e_i|$ which simply requires the sum of the absolute values of the error term to be minimised. For all other quantile values, the equation can be expanded by making the error term from the original quantile regression equation the subject of that equation $[e_i = y_i - x_i'\beta_q]$ and substituting. This gives:

$$Q(\beta_q) = \sum_{i:y_i \geq x_i'\beta}^{N} q\,|y_i - x_i'\beta_q| + \sum_{i:y_i < x_i'\beta}^{N} (1-q)\,|y_i - x_i'\beta_q| \tag{B.7}$$

The first term is a penalty term of q for under-prediction, where the actual value of y_i is higher than the predicted value $x_i'\beta_q$. The second term is a penalty term of $(1-q)$ where the actual value of y_i is lower than the predicted value $x_i'\beta_q$. The quantile regression model minimises the above function using linear programming methods.

For OLS regression models, there are commonly used methods to select the predictor variables that should be included in the final model. This is not so for quantile regression and it should be borne in mind that predictor variables that may be usefully included in the 0.1 quantile model could need to be excluded from the 0.9 quantile model.

A quantile regression software package called ‘quantreg’ was developed for the statistical software R (R Development Core Team, 2010) and is able to calculate quantile regression together with confidence intervals. As the characteristic values of bending strength and density in timber grading are determined by the calculation of the lower 75% confidence limit of the 5-percentile value, these two calculations are considered to be most useful attributes of the software.

In ‘quantreg’, the quantile level is termed tau (τ) and for each tau level there is a distinct set of regression coefficients. The ‘quantreg’ package also produces quantile process plots showing parameter estimates at varying quantile values enclosed within a 95% confidence band. This allows a comparison between the varying values of quantile regression coefficients (including confidence limits) with the equivalent values (relating to the mean) obtained from OLS regression. The OLS regression coefficients are shown on the graphs, as straight, horizontal lines (as these do not vary according to the quantile values). Where the quantile regression lines lie outside the OLS regression line confidence interval, then there is a significant difference between the two coefficients.

B.5 Finding the 0.05 quantile of a conditional distribution

The basis of quantile regression is explained in the section above and the carrying out of the calculations to determine the quantile of a distribution is done by software. The method used can provide an estimate of the 0.05 quantile of the distribution of the dependent variable for each individual predictor variable or combination of predictor variables.

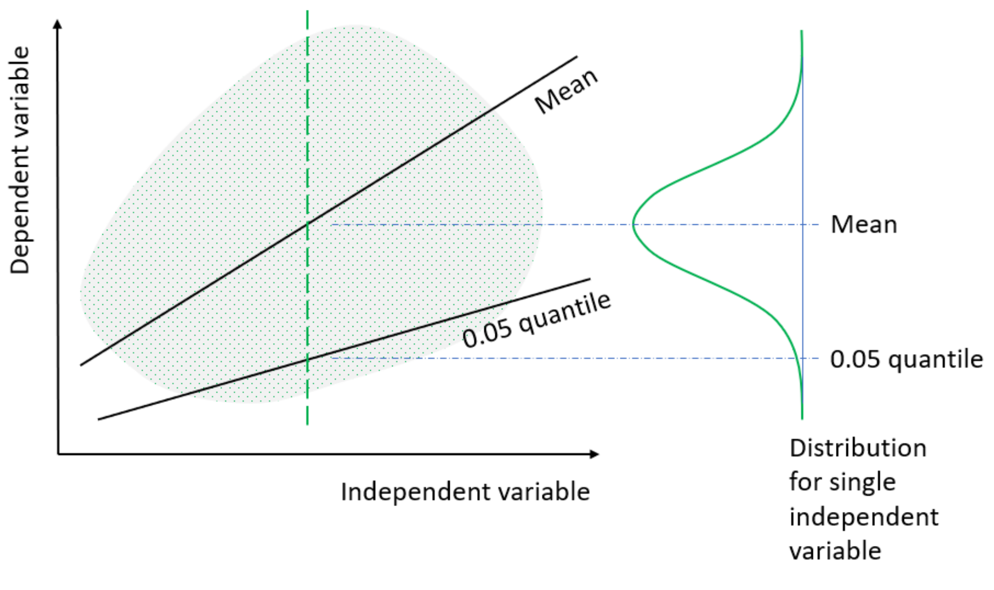

Figure B1. Simplified illustration of the 0.05 quantile of a conditional distribution using quantile regression

This is a non-parametric method which makes no assumptions as to the distribution of the dependent variable in relation to any particular set of predictor variables (or set of predictor variables). Nevertheless, the method provides a standard error, with which it should be possible to construct a confidence interval around the quantile regression estimate.

B.6 Finding the confidence interval around the 0.05 quantile of a conditional distribution

The confidence interval around the 0.05 quantile of a conditional distribution could be calculated using OLS regression, firstly estimating the mean and then the 0.05 quantile and then by making assumptions as to the sampling distribution and finally, by using the noncentral t distribution together with the standard error of the model. The approach would be the same as for finding the confidence interval around a quantile of a sample and the equation is expressed in words as

$$'sample\ quantile\ estimate\ \pm\ t - mulitiplier\ \times\ standard\ error'$$

$$LCL\ =\ \bar{y} -\ t_{(1-\ ^{\alpha}/_{2}\ ;\ n-1\ ;\ \delta)}\ \times\ SE \tag{B.8}$$

To make use of this formula, the t-multiplier would need to be determined (again, just as for the confidence interval around a quantile of a sample). The t-multiplier would be the $\left(1 - {}^{\alpha}/_{2}\right)$ quantile of a noncentral t-distribution with $n-1$ degrees of freedom and noncentrality parameter δ . To determine this multiplier, an assumption would need to be made about the sampling distribution.

Despite the standard error being provided by the quantreg() package (used in r to determine the 0.05 quantile), it could not simply be applied with an appropriate t or z score to give upper and lower bounds of a confidence interval. As noted above, due to the non-symmetrical nature of the probability distribution around the quantile, the upper and lower limits are calculated to be at different distances from the quantile, with the lower confidence limit being located further from the 0.05 quantile than the upper.

However, no assumptions about sampling distributions are necessary when a non-parametric approach is adopted which also has the benefit of maintaining a consistent approach (i.e. determining the quantile and then its confidence interval both using non-parametric approaches). The boot package in R has two functions boot() and boot.ci() which allow the confidence limits of a statistic to be determined using bootstrapping.

Bootstrapping is a method of resampling using random sampling with replacement. It creates an empirical distribution of a statistic and as such is useful for the estimation of a confidence interval. The method for determining the confidence limits around a quantile is described in outline below. Each of the steps requiring many calculations are performed by the software R and only take a few seconds.

Using the original data set of 527 observations, choose two or three predictor variables and then create a quantile regression model for the 0.05 quantile. This model has a set of coefficients for intercept and for the slope of each predictor variable, and these coefficients relate to the particular data points in the data set.

Then a second set of 527 observations is created by resampling with replacement. Using this second, slightly different data set, a second quantile regression model is created with a slightly different set of coefficients for intercept and slopes.

Then, a third data set is created in the same fashion and used to create a third model with slightly different coefficients. This pattern is continued until a large number (e.g. 1000) data sets and corresponding models are created.

Then for a given set of predictor variables, and using the say, 1000 models, 1000 estimates of the independent variable (the 0.05 quantile) can be made. The distribution of these estimates can be ranked and percentiles of the estimates can be determined. Thus, for instance, the upper and lower 90% confidence limits for an estimate (for a given set of predictor variables) would be the equivalent to the 5th and 95th percentiles of the 1000 estimates produced from the 1000 bootstrapped samples.

As the Eurocodes require the estimation of the lower limit of a 50% two sided confidence interval around the 0.05 quantile for both density and MoR, the above method is used in this study. The two chief benefits of using this bootstrap method are (i) the lack of a need to know the sampling distribution of the quantile and (ii) the transparency of the method.

Despite the large volume of data points 'created' for the bootstrapping analysis, it must be borne in mind that this does not improve the actual size of the sample nor its quality. The fact that this sample is not representative of the entire population of in situ structural timber in the UK is not changed by bootstrapping and creating potentially several thousand new data sets.

Appendix C EN1912 Visual grades linked to strength classes

EN1912 has only a limited number of species and growth areas linked with species and strength classes. The four minor species in this study and their growth areas are not directly linked. The table below is extracted from EN1912 is amended to show the most relevant data which are used in this study to create links for the purpose of allotting strength classes to the four minor species. The shaded cells of the table are considered to be the most relevant.

Genus	EN1912 ID No	C30	C30	C24	C24	C24	C18	C18	C18	C16	C16	C14	C14
		DIN	INSTA	BS	DIN	INSTA	BS	DIN	INSTA	BS	DIN	BS	INSTA
Spruce	22	S13 (CNE)	T3 (NNE)	SS (CNE)	S10 (CNE)	T2 (NNE)	SS (UK) SS (IRLD)	S7 (CNE)	T1 (NNE)	GS (CNE)		GS (UK) GS (IRLD)	T0 (NNE)
Hemlock	62			SS (U&C)						GS (U&C)			
Cedar	58						SS (CAN)					GS (CAN)	
Fir	1	S13 (CNE)	T3 (NNE)	SS (CNE)	S10 (CNE)	T2 (NNE)			T1 (NNE)	GS (CNE)	S7 (G&A)		T0 (NNE)
Larch	15	S13 (CNE)	T3 (NNE)	SS (UK)	S10 (CNE)	T2 (NNE)			T1 (NNE)		S7 (CNE)		T0 (NNE)
Pine	47	S13 (CNE)	T3 (NNE)	SS (CNE)	S10 (CNE)	T2 (NNE)		S 7 (CNE)	T1 (NNE)	GS (CNE)			T0 (NNE)
Fir	54				S10 (CNE)		SS (UK)				S7(G&A)		
Spruce	28					T2 (D&N)	SS (IRLD) SS (CAN) SS (UK)		T1 (D&N)			GS (IRLD) GS (CAN) GS (UK)	T0 (D&N)
Larch	15,16,17			SS (UK)						GS (UK)			
Fir-Larch	18,54			SS (U&C)						GS (U&C)			
Pine	39,47											GS (UK)	
Fir-Spruce-Pine-Hemlock	3,6,23,34, 37,38,45,63						SS (USA)					GS (USA)	
Hemlock-Fir	2,4,5,7,8,62			SS (U&C)						GS (U&C)			
Spruce-Pine-Fir	3,6,23,25,26, 27,32,34,45			SS (U&C)						GS (U&C)			
Pine	35,36,43,48			SS (USA)			GS (USA)						

Figure C1. Extract from EN1912, visual grades linked to strength classes for genii associated with the four minor species

Appendix D Further information on building the predictive model for the lower confidence limit of mean MoE

D.1 Introduction

The purpose of this appendix is to supplement Chapter 8 by presenting more details of the model building process for the determination of the lower two sided 50% confidence limit of the mean of MoE (MoE_{LCL}) for individual joists. As is mentioned in the main body of the thesis, as well as the 'best' predictive model for mean MoE_{LCL} a series of other models for mean MoE_{LCL} are created using single and multiple predictor variables. When assessing a structure on site, it may not be possible to measure every one of the variables in the 'best' model, however, it may be possible to measure one or more of the variables. Reference should be made to Chapter 5, which gives both those measurements used in this study for knots and variants that may be the best that can be achieved on site.

For instance, in this study, it was easy to pick up a joist, turn it in one's hands and carefully assess all six faces of the joist in good lighting to determine its knot measure. On site, perhaps, only two vertical wide faces may be accessible.

So, it is useful to consider the strengths and weaknesses of each of the variables individually and as such, their estimates can more easily be seen graphically. Having created a series of predictive models, their efficacy is compared and the weaker models are considered in more detail; is it reasonable to use these weaker models and if so, are any adjustments required to ensure conservative outcomes?

D.2 MoE OLS regression 'best' model building

This section covers the building of the 'best' predictive model for MoE based on OLS regression while ensuring that the requirements for OLS regression are met and that for instance, outliers are adequately considered. Building a model to predict MoE based on a short list of independent variables involves several stages:

1. Choose useful predictor variables for the model
2. Consider the relationships between the variables in the potential multiple regression model
3. Check the underlying assumptions of the OLS regression (including multicollinearity) and then carry out any necessary corrective measures
4. Potentially refine the model by considering polynomial variables (such as $\sqrt{x}$ *and* x^2 *and* $\ln x$ in place of just x); this kind of transformation may be required in any case as a corrective measure
5. Consider both interactions between variables (x:y) and interactions between predictors; considering outliers and influential points
6. Assess the predictive power of the model (possibly amending it to improve it) using k-fold cross-validation

D.2.1 Predictor variables

Even before commencing upon the first of the items on the numbered list above, time was spent choosing the most useful measures of knots in relation to MoE. Reference should be made to Sub-section 5.3 which explains the method of selection of the knot group parameter kg3. This is a measure of all knot diameters (with no accounting for overlapping knots) over a length of 400mm of a timber joist.

The statistical software package R is well suited to perform all the steps listed above and the way that the model was built is described below. The choice of predictor variables is drawn from the dynamic modulus of elasticity (MoE_{dyn}), density, the knot group ratio kg3, the number of growth rings in a given length (RoG) and finally, slope of grain (SoG). These are the NDT and SDT grading parameters identified in Chapter 5 as having the strongest correlations with MoE.

Of all the possible predictor variables, the most useful can generally be most easily identified using two functions; from the leaps R package: plot() and from the car R package: subsets(). Initially, the subsets() function was run to show the best combinations of predictor variables. This indicates that 11 combinations of predictor variables have adjusted coefficients of determination, r^2, of 0.91 and that a further 3 combinations give values of 0.90. In the best three performing combinations, RoG and/or density are omitted in two of the three combinations, suggesting that these predictors may be considered for omission. Only MoE_{dyn} and kg3 appear in all of the top eight combinations, suggesting that these predictors are most useful. The three variable combination (MoE_{dyn} kg3 and SoG) has one of the highest of all adjusted r^2 values, and there is little to differentiate it from the other larger combinations (of four or five variables) with slightly higher adjusted r^2 values. In short, at this point, the three variable combination (MoE_{dyn} kg3 and SoG) looks the best for the predictive model (using only the data from the minor species) but requires more analysis.

Next, the Mallows Cp statistic is used in an attempt to differentiate between the best models. This is a measure of the relative fit of an OLS regression model that accounts for the number of predictor variables. Lower values of the Cp statistic indicate greater precision in the model and it is suggested that a Cp statistic close to the number of model parameters (including the intercept) indicates a good model (Kabacoff, 2015). From this, the combination with three predictor variables (MoE_{dyn} kg3 and SoG) is seen to have the lowest Mallows Cp value of all and is investigated as a possible 'best' model.

D.2.2 Relationships between the variables in the model

As it appears likely that the final model will involve multiple linear regression, it is appropriate to consider the relationships between the predictor variables two at a time. From the car package in R, the function scatterPlotMatrix() allows the bivariate correlations to be examined graphically. Visually assessing the variables is an important step in understanding the data being used.

The principal diagonal in Figure D.1 shows the density and rug plots for each variable (a rug plot simply shows a tick along the x axis for each data point, giving a one dimensional representation of the data points). It is seen that MoE and MoE_{dyn} have broadly symmetrical distributions but that the other variables have longer tails to the right indicating slight positive skewness.

Above and below the principal diagonal are two sets of bivariate scatter plots. Only one of the scatter plots shows a strong linear relationship between two variables: MoE and MoE_{dyn}. All other scatter plots show a spread of results which are typically linear or with a gentle curve.

The scatter plots for MoE with kg3 and for MoE with RoG show a slight gentle curvature, indicating that some form of transformation of the variables could be worthwhile. This is later investigated (both square and inverse square) and shows no improvement in the strength of the linear relationship between the variables.

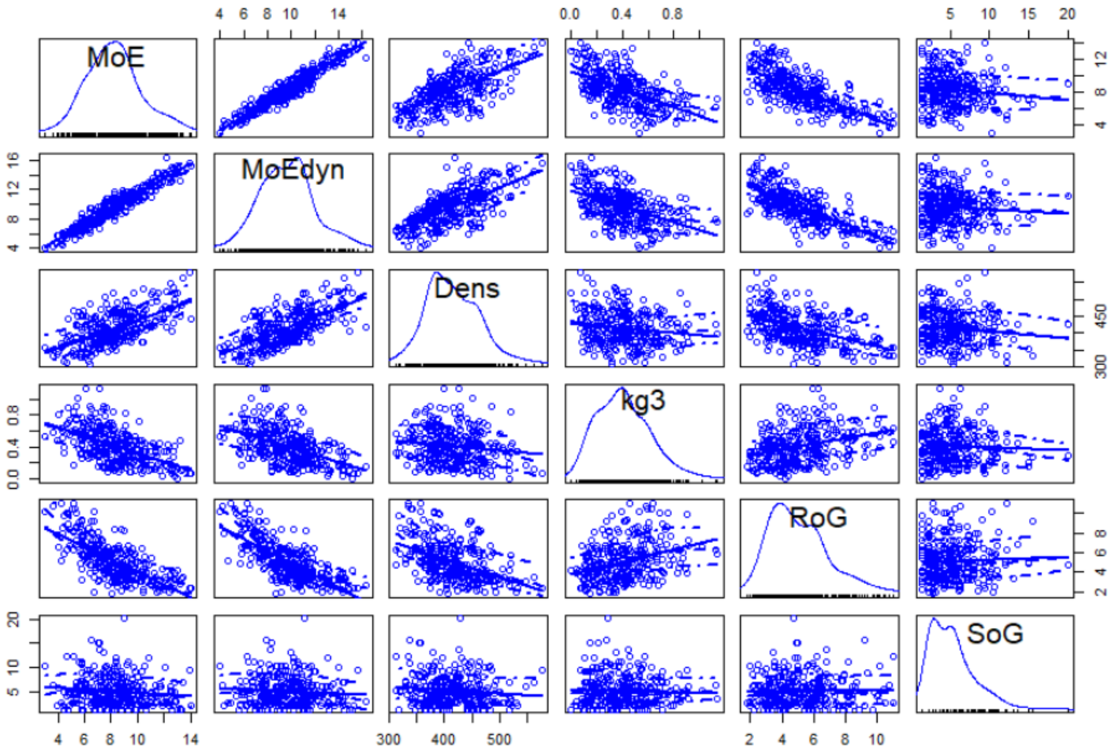

Figure D.1. Scatter plot matrix of dependent and predictor variables including linear and smoothed fits and marginal distributions (kernel-density plots and rug plots) based on 317 data points (including all SoG and RoG results)

Having viewed the bivariate relationships graphically, it is now useful to consider the dependent variable with each predictor variable one at a time. The cor() function calculates Pearson's correlation coefficient for each of these relationships in turn and these are presented in Table D.1. These show MoE_{dyn} as the best individual predictor and SoG as the worst with density, knot measure and RoG in between.

Table D.1. Bivariate correlation coefficients between the predictor and dependent variables, two at a time

	MoE	MoE_{dyn}	Dens	kg3	RoG	SoG
MoE	1.00	0.95	0.62	-0.54	-0.70	-0.12
MoE_{dyn}	0.95	1.00	0.65	-0.49	-0.73	-0.08
Dens	0.62	0.65	1.00	-0.15	-0.45	-0.12
kg3	-0.54	-0.49	-0.15	1.00	0.34	-0.05
RoG	-0.70	-0.73	-0.45	0.34	1.00	0.05
SoG	-0.12	-0.08	-0.12	-0.05	0.05	1.00

D.2.3 Underlying assumptions

A preliminary OLS model is now created and tested, firstly to ensure that it does not violate any necessary assumptions and secondly, to potentially improve the format of any of the variables through transformation.

Once a preliminary OLS model is created, using the lm() function, it is possible to perform a global validation of its inherent assumptions. From the gvlma R package, the function gvlma() assesses the linear model assumptions and after presenting a single global statistic (Peña and Slate, 2006), it gives a simple go/no go output for skewness[4], kurtosis[5] and heteroscedasticity[6].

The linear model using all predictor variables indicates that neither density nor RoG are significant at the $p < 0.05$ level and that both MoE_{dyn} and the knot measure kg3 are significant at the $p < 0.0001$ level. SoG is significant at the $p < 0.01$ level. The gvlma() function calculates a global statistic of 4.06 with a p value of 0.40 and the decision line indicates that none of the assumptions of OLS regression are violated, with the lowest

[4] Skewness is a measure of the symmetry of a probability distribution

[5] Kurtosis is a measure of the weight of the tails of a distribution relative to a normal distribution

[6] The data points of a homoscedastic distribution have a constant degree of scatter and a constant variance of the residual in a regression model. Conversely, a distribution with a varying degree of scatter and changing variance of the residual is heteroscedastic.

p value being 0.20. This is a good start, however, as the gvlma package is relatively new and reportedly, relatively little used in the R community (Mueller, no date), it is still worthwhile to carry out the normal diagnostic plots as confirmation.

The confidence intervals for the intercept and slope of the linear model were calculated and those for RoG and density are seen to contain zero, showing weak relationships with MoE.

Normality is visually assessed using a quantile-quantile plot (Q-Q plot) which is created using the qqPlot() function from the R package car. This plots the studentized residuals[7] against a t distribution with $n - p - 1$ degrees of freedom, where n is the sample size and p is the number of regression parameters. Figure D.2 shows the Q-Q plot with 95% confidence limits, produced using a parametric bootstrap method. This shows that most of the data points lie close to the principal diagonal and between the confidence limits, which is an indication of normality. Finally, the distribution has a calculated skewness statistic of 0.37 and a kurtosis statistic of -0.12, which are both close to zero and strong indications of normality.

[7] Studentized residuals result from the division of a residual by an estimate of its standard deviation and are useful in detecting outliers

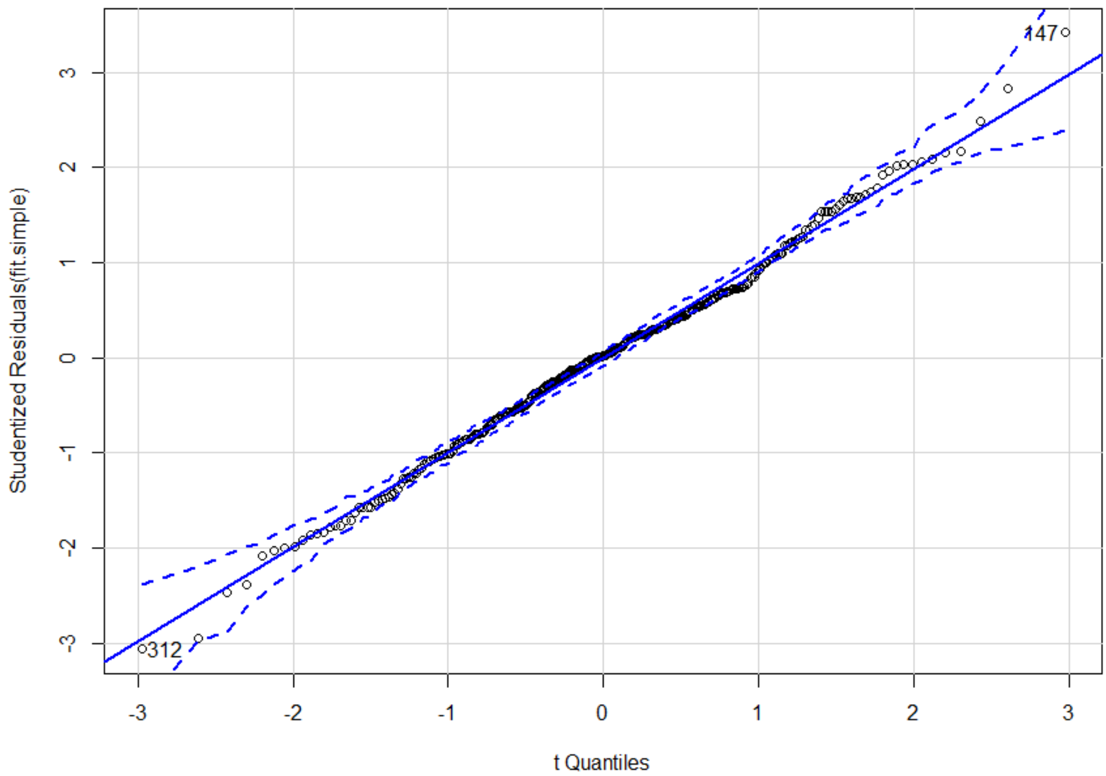

Figure D.2. Q-Q Plot with studentized residuals for the multivariate linear model using all predictor variables

The assumption of independence of errors is best assessed by considering the dependent variable, using common sense and an understanding of the sampling procedure. The sample comprises joists that were cut from four different species (Norway spruce (NS) , noble fir (AP), western red cedar (RC) and western hemlock (WH)), from three locations (North (N), Middle (M) and South (S) sites in Scotland, Wales and England).

It would be reasonable to consider that joists of the same species grown in the same location will exhibit similar properties (after all, visual grading codes used around the world are at least partly based on this assumption). Also, the possibility that joists cut from the same tree have similar properties should also be investigated. However, reference should be made to the literature review of Chapter 2 (in particular, regarding the Gradewood Project) and to the thesis based on the minor species sample (Gil-Moreno, 2018) in which sources of variation are investigated. Together, these show that the error terms of any models will vary independently and that any similarities based on species, site location or radial position are not sufficient to affect the OLS model.

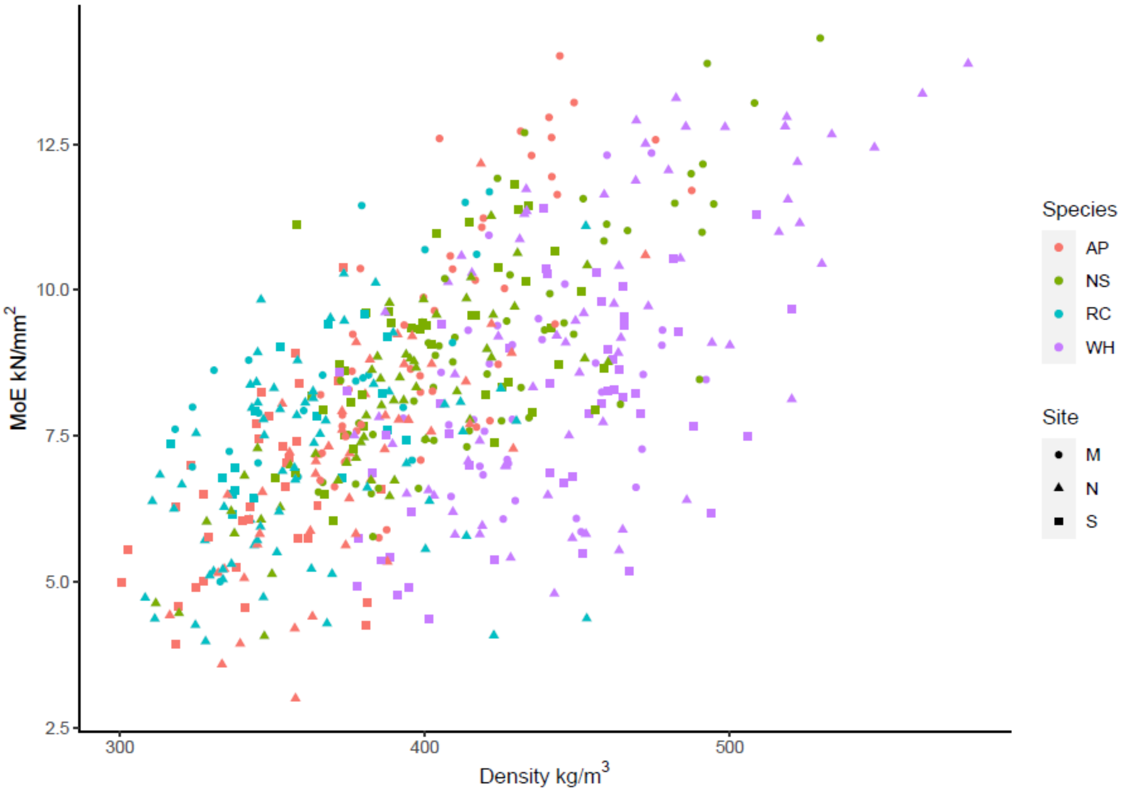

Figure D.3. Scatter plot comparing density with MoE and differentiated by species and site (n=527)

This is seen visually in Figure D.3 which shows much overlapping between species and sites. From a visual inspection of the graph, western red cedar is shown to be less dense and less stiff in comparison with the other species and western hemlock is seen to be denser. It is not possible to see any trends with regard to sites.

Descriptive statistics of MoE by species confirm the skew of noble fir as being the largest of the group at +0.54 and the kurtosis of western hemlock being the smallest at -0.67. Neither of these descriptive statistics indicate significant deviation from the normal distribution.

It is reported in the literature that the mechanical and physical properties of joists cut from trees vary in relation to the radial position of each joist. This within-tree variation was also noted informally during the laboratory testing. The Brown-Forsythe test is a non-parametric test that compares the dispersion of the data points in each sub-set to its median and it gives an indication of the variation between factors. The output of this test indicates that variation in MoE does not differ significantly either between sites or radial positions, however variation is significant between species (F value =

2.21, 3 degrees of freedom and p-value < 0.01). This variance between species can be considered to be a useful attribute of the sample as it reflects the variations between the many species of in situ timber joists found in the population of all timber joists in existing structures.

The assumption of linearity is assessed by considering the relationship between the dependent variable and the predictor variables using 'Component plus residual plots' created using the crPlot() function from the R package car. The five graphs in Figure D.4 show the residual values relating to each separate predictor variable as data points, the corresponding linear model is a straight dashed blue line and the curved pink line is a smoothed non-parametric fit line created by the loess() function in R. For the assumption of linearity to hold true, the smoothed fit line should be broadly linear.

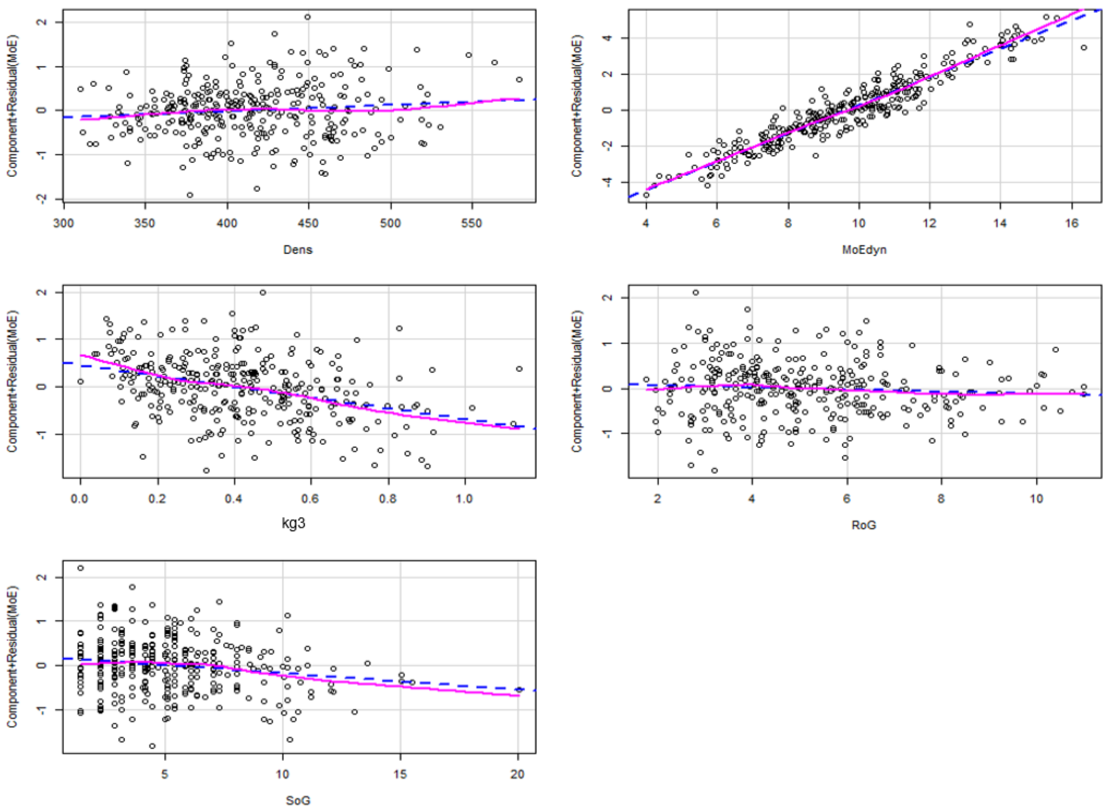

Figure D.4. Five component and residual plots assessing linearity in the simple OLS model predicting MoE

It is apparent from Figure D.4 that linearity is present for all five predictor variables and so the linearity assumption is satisfied. This suggests that no transformation of these predictor variables (such as ln(SoG) or $(RoG)^2$) is required.

The assumption of homoscedasticity can be assessed by creating a test score for the variance of the error of the fitted model compared to that for an idealised model with constant size of error regardless of the level of the fitted values. This is done using the ncvTest() function from the car package in R. A low p-value indicates a significant difference between these variances and for the simple OLS model. This test returns a chi-squared value of 5.64 and a significant p-value of 0.02 which indicates a small degree of heteroscedasticity.

The degree of heteroscedasticity is illustrated graphically in the scatter plots of Figure D.5 showing the fitted values of two simple linear models plotted against the absolute studentized residuals (with a straight line of best fit and a smoothed non-parametric fit line superimposed). The upper graph has a plain dependent variable of MoE and the lower graph has a transformed dependent variable of the square root of MoE $\left(\sqrt{MoE}\right)$.

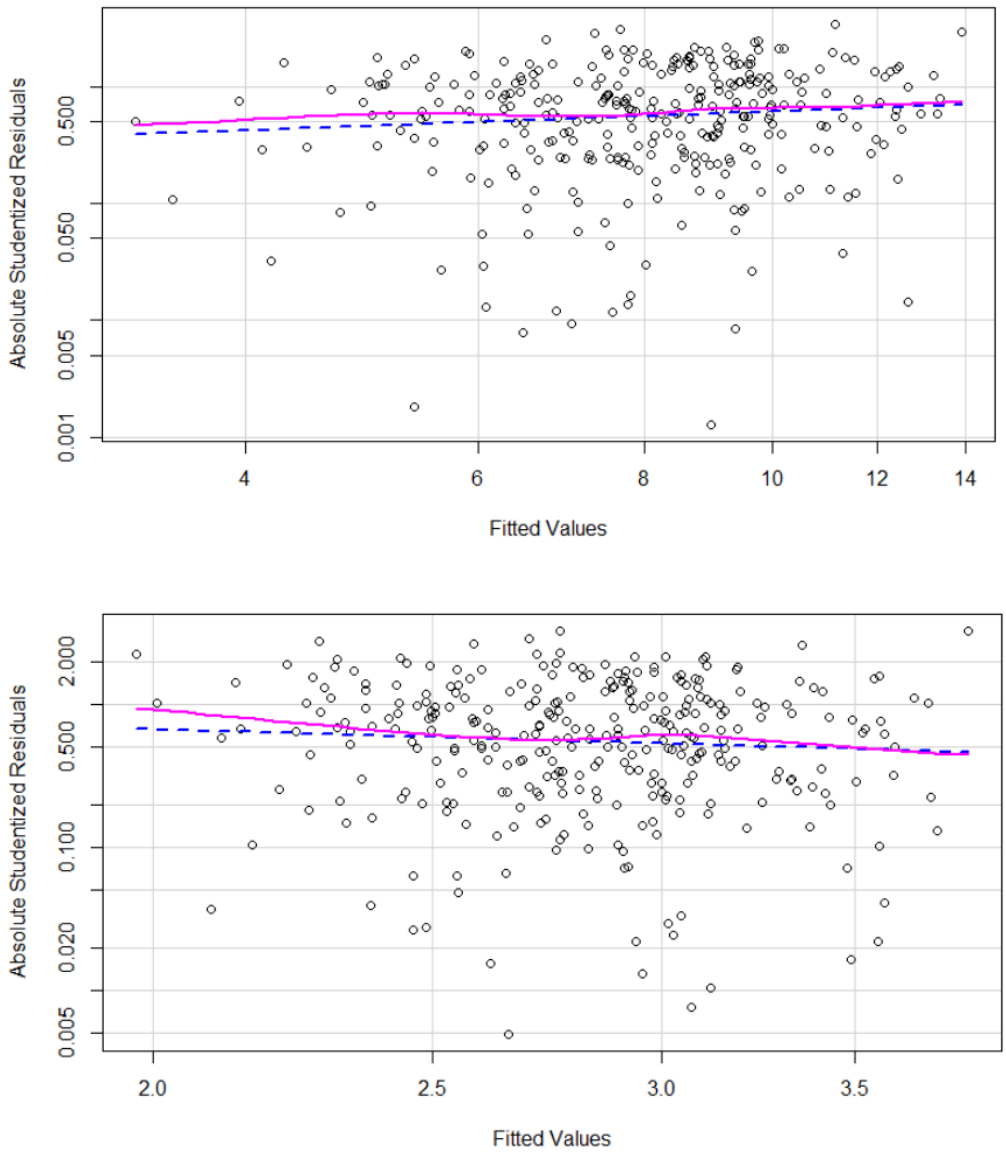

Figure D.5. 'Spread-Level' plots of absolute studentized residuals plotted with the straight line of the OLS model and the curved, smoothed non-parametric fit line

In Figure D.5, the upper graph shows less homogeneity than the lower graph but the near horizontal lines in both graphs suggest that the degrees of heteroscedasticity are not large. The spreadLevelPlot() function suggests that it would be worthwhile to explore the power transformation of the plain dependent variable of 0.59.

D.2.4 Polynomial variables and transformations

The function powerTransform() from the R package car implements the Box and Cox (1964) method of selecting a power transformation of a variable toward normality. The possible improvements to be gained through power transformation were assessed using this function which suggested a power transformation of MoE to the power of 0.46 (which is close to the 0.59 value suggested by the spreadLevelPlot() function) to create a more normal distribution for the dependent variable. Both these suggested powers approximate to the power of 0.5 and hence, as a trial, the dependent variable is transformed to its square root $\left(\sqrt{MoE}\right)$ and the graph in Figure D.6 show the results of the transformation. Each standardised graph has a standard deviation of one and a mean of zero. Neither of the two overlaid graphs have perfectly normal distributions and neither appears to be significantly better than the other. The apparently marginal improvement through transformation of the dependent variable is borne out in several statistical tests.

The ncvTest() function confirms that the transformed dependent variable improves the homogeneity of the model but the spreadLevelPlot() function recommends that the transformed dependent variable $\left(\sqrt{MoE}\right)$ be transformed by the power 1.62, which effectively means squaring this value, returning it to it untransformed state.

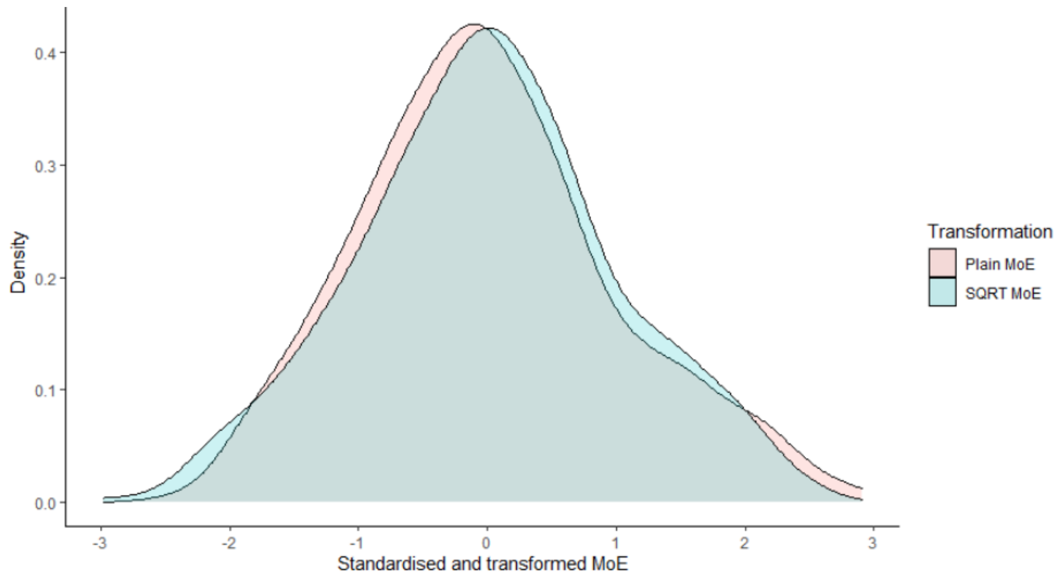

Figure D.6. Overlaid density curves showing a slight difference in normality. The pink graph is MoE and the blue graph is $\sqrt{MoE}$

The transformed linear model with $\sqrt{MoE}$ as the dependent variable fares worse than the original plain linear model, as is shown by the output of the gvlma() function: a calculated global statistic of 17.41 with a p value of 0.002 indicating that overall, the assumptions for the transformed model are not satisfied. Also, there is little difference to be seen between the component and residual plots of the two models using the plain and transformed dependent variables.

Finally, for the transformed linear model, the powerTransform() function suggests that the most appropriate power transformation for independent variable $\sqrt{MoE}$ is to the power 1.56, which effectively is to square it, returning us back to plain MoE. Bearing in mind the mixed indicators, it is concluded that no transformation will be applied to MoE and this outcome accords well with the literature review.

D.2.5 Interactions between variables and between predictors and outliers

Multicollinearity was checked to ensure that the strength of correlations between the predictor variables is not so great as to adversely affect the OLS model. The presence of multicollinearity can lead to the calculation of overly large confidence intervals and it can be checked with reference to a statistic called the variance inflation factor (VIF). The statistic can be found using the vif() function of the car package in R. As the highest VIF statistic obtained for any of the predictor variable was only 3.65 (which is less than a marker value of 4), it is concluded that there are no multicollinearity problems with the data.

Outliers (observations that are poorly predicted by the model), high leverage points (data points with unusual combinations of predictor variables) and influential observations (data points which exert a strong effect on the OLS model) are assessed using a range of functions in R from the car package. As already indicated by the QQ plot and confirmed using the outlierTest() function in R (which reports the Bonferroni adjusted p-value for the largest absolute studentised residual), no outliers were identified for the simple multivariate OLS model. Hat statistics were calculated for each of the data points and plotted on a graph in Figure D.7. Two high leverage points were identified which merit further investigation.

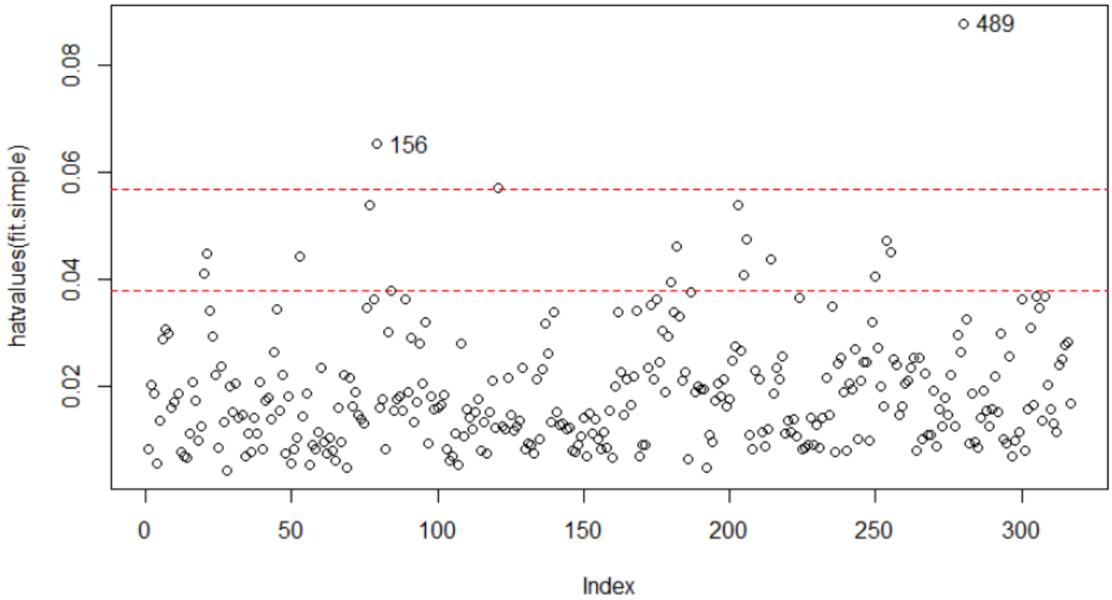

Figure D.7. Index plot of hat values showing data points with high leverage in the simple OLS model for MoE. The dashed red lines are drawn at 2 and 3 times the average hat value.

Cook's distance was also calculated for each data point and three data points are significantly higher than the typical marker level set at $\frac{4}{n-k-1}$, where n is the sample size and k is the number of predictor variables. It is noted that a cut off level of 1.0 for this statistic is commonly used and, on this basis (with the largest value calculated being less than 0.1), it is concluded that there are no influential data points (Kabacoff, 2015). Nevertheless, it is worthwhile to investigate a little further the three 'influential' observations along with the two high leverage points.

Table D.2 presents key data for the observations in question along with the sample mean and upper and lower confidence limits for 95% of values in the sample. Two of the three 'influential' joists are seen to have particularly high values of MoE, MoR and MoE_{dyn} and the third joist has a very high knot ratio. The MoE_{dyn} correspond well with high values of MoE and MoR. The high value of the knot ratio corresponds well with notes made in the laboratory and with the slightly below average values of MoE and MoR.

Table D.2. Table of influential and high leverage observations identified for the simple OLS multivariate model to predict MoE. Grey shaded cells indicate values that lie outside the 95% sample confidence limits (calculated using the full data set of 527 observations where possible)

Joist ID / statistic	MoE	MoR	Dens	MoE_{dyn}	Kg3	RoG	SoG	Notes
	kN/mm^2	N/mm^2	kg/m^3	kN/mm^2	Ratio	%	%	
Mean	8.2	35.2	402	9.4	0.38	5.0	5.2	
Upper confidence limit	12.3	58.2	500	14.0	0.78	8.9	11.0	
Lower confidence limit	4.0	12.1	305	4.8	-0.02	1.0	-0.5	
Influential observations								
SAP9-4	12.2	64.3	418	16.3	0.16	2.7	3.2	Horizontal shear failure about 60mm above bottom tension face of joist. Some radial and cross grain splitting of the timber on the tension bottom face.
MAP1-5	13.2	68.3	449	13.1	0.47	2.8	1.4	Cross grain cracking starting close to a bottom edge knot where SoG is locally very steep. Stepped cross grain cracking between earlywood and latewood
MAP7-1	7.1	29.4	399	7.6	1.14	5.9	3.6	Tension cracking amid cluster of knots
High leverage data points								
SAP1-4	6.5	26.9	335	7.9	0.27	9.2	15.5	Horizontal shear failure apparent and not possible to see tension or other cross grain cracking
DWH2-5	9.0	47.7	428	11.1	0.29	4.7	20.0	Mostly tension cracking with a little cross grain cracking at the bottom edge leading to shear cracking following curving grain up to the top of the joist

The high leverage points in the table have very high SoG values and for one joist (SAP1-4), they correspond well with below average MoE and MoR. The final joist has a particularly high value of SoG which combines with a below average RoG which would be expected to indicate lack of stiffness and strength, but this joist (DWH2-5) is above average in these respects. Both of these joists failed at least in part in shear.

It is concluded that neither the influential observations nor the high leverage data points merit being deleted from the data set as the variance in their behaviour is not untypical of timber testing in general. It should be noted that a model built upon the median of the data set and calculated using quantile regression, rather than the mean (which is the case for OLS regression), would be more robust to these influential and high leverage observations.

When the relationship between one predictor variable and the dependent variable depends on the level of another predictor variable there is said to be an interaction between the two variables. On occasion, an OLS model can be improved by including interactions between predictor variables and so several OLS models were checked considering interactions between predictor variables. Interactions between MoE_{dyn}:kg3 and MoE_{dyn}:SoG and kg3:SoG were checked and were found to reduce the power of the model. Therefore, no interactions are considered further.

Additionally, on occasion the transformation of one or more predictor variable can improve an OLS model. The boxTidwell() function of the R package car calculates the maximum-likelihood estimates of transformation of the predictors in an OLS model using Box and Tidwell's (1962) method. This function was applied and the lowest p-value for any of the predictor variables was calculated to be 0.22. These relatively high p-values indicate that we accept the null hypothesis that no power transformation is required. Thus, all of the variables will be used without transformation. This outcome accords well with the literature review.

It is worthwhile to consider the relative importance of each of the predictor variables. As predictor variables are expected to be correlated with each other, it is not possible to simply compare the correlation of each predictor variable with the dependent variable in turn and then place in rank order. In this instance, standardised regression coefficients are used, which describe the expected change in the dependent variable for a unit change in the predictor variable of interest, while holding all other predictor variables constant. Units used for this standardised calculation are standard deviations. To carry out the comparison, the scale() function in R is used to standardise each of the variables to a mean of zero and standard deviation of 1.

Table D.3. Ranked standardised regression coefficients for predictor variables showing relative importance

Predictor variable	Standardised regression coefficient
MoE_{dyn}	1.816
kg3	0.242
SoG	0.110
Density	0.066
RoG	0.047

The values in Table D.3 summarise the outcomes of the above procedure and show that MoE_{dyn} and kg3 are the most important predictor variables and SoG, Density and RoG predictor variables have smaller effects on the OLS model. The best predictor variable by far is MoE_{dyn}, and for 1 standard deviation change of MoE_{dyn}, MoE will change by 1.816 standard deviations. Removing density and RoG from the model barely changes the relative importance of the remaining predictor variables.

D.2.6 Predictive power of the models and the predictive equation

The OLS model is constructed using the data from the sample of 527 observations and is fitted to this data. As the purpose of the model is to predict the MoE of timber outside this sample, it is important to consider how well the model can predict using new data. In the future, this model can be applied to new data sets and reviewed and revised accordingly. For the purposes of this study, this is not possible and so cross-validation is used. The data set is split into a training set and an assessment set.

The sample is split into k sub-sets and each of these k sub-sets are used as the assessment set in turn with a training set comprising the other $k - 1$ sub-sets. The performance of the k OLS models is recorded and averaged to give a k-fold cross validated value of the coefficient of determination, r^2. This inevitably will be less than the value of the coefficient of determination for the entire set of observations. The difference between the two r^2 values can be found to illustrate the reduction in power of the OLS model from describing the entire data set to predicting values in a sub-set of the entire data set. The bootstrap() function of the R package bootstrap is used to do this.

Table D.4. Coefficients of determination, r^2, and adjusted r^2 values based on k-fold cross validation (k = 10) for the prediction of MoE (n = sample size, p = number of predictor variables)

Predictor variables	n	p	r^2	Adjusted r^2	AIC
MoE_{dyn} + kg3 + SoG + Dens + RoG	317	5	0.916	0.912	605
MoE_{dyn} + kg3 + SoG + Dens	317	4	0.916	0.912	603
MoE_{dyn} + kg3 + SoG	317	3	0.915	0.912	603
MoE_{dyn} + kg3	317	2	0.913	0.910	612
MoE_{dyn} + kg3	527	2	0.908	0.906	1035
MoE_{dyn}	527	1	0.897	0.896	1093

All of the values of the coefficient of determination from the k-fold cross validation in Table D.4 are very similar to the r^2 value based on the whole sample. The adjusted r^2 values in turn are generally very similar. This indicates firstly that the standard approaches to differentiate between models are of limited help in this situation and secondly, that, based on these approaches, there is little to choose between using two predictor variables and using three. This accords with both the Mallows Cp statistics and the standardised regression coefficients, calculated earlier. For the smaller sample of n=317, the model with three predictor variables is marginally the best.

Akaike's Information Criterion (AIC) statistic (Akaike, 1973) is calculated using the AIC() function in R and the lower its value, the more parsimonious is the fit of the OLS model, which is generally to be preferred. The AIC statistic cannot be used to compare models based of differing sample sizes and so the AIC values of the bottom two rows of the table should not be compared with the others. On the basis that simpler models that perform similarly to more complex models are to be preferred, the predictors density and RoG should not be included in the OLS model. The predictors MoE_{dyn} and kg3 should definitely be included in the model and finally, there is a slight indication that the predictor SoG should be included. Research on other species suggests that the ‘best’ model should only include the single predictor MoE_{dyn} (Arriaga *et al.*, 2014), and so it should be noted that discussion here is limited to the four minor species.

Based on the limited data set and from the statistical tests used, there is little to choose between the various combinations of predictor variables. This strengthens the argument for creating a range of predictive models which can be applied according to the needs of a structural appraisal. As the predictive models’ data set is expanded in the future, the relative power of different models will need to be reviewed.

Reference should be made to Chapter 2, which discusses the variance of the mechanical and physical properties of timber from different growing regions and the improved generalizability of models with more predictors than less. Thus, the slight preference to include SoG in the model is reinforced by the literature review. So, despite the poor correlation of SoG on its own with MoE and its lack of real impact on the OLS model, it is decided to include this predictor variable and to focus on an OLS model based on the predictors MoE_{dyn}, kg3 and SoG. This is investigated and a model is developed to estimate the mean MoE value for all values of MoE_{dyn} (together with the associated values of kg3 and SoG) from the sample.

$$Estimated\ mean\ MoE = 0.979 + 0.820\, MoEdyn - 1.065\, kg3 - 0.038\, SoG \qquad \text{(D.1)}$$

The lower two sided 50% confidence limit (LCL) for this model is given in the equation below.

$$MoE_{LCL} = 0.947 + 0.820\, MoEdyn - 1.072\, kg3 - 0.040\, SoG \qquad \text{(D.2)}$$

In summary, this predictive model estimates the lower two sided 50% confidence limit for MoE (MoE_{LCL}) of an individual piece of timber based on MoE_{dyn}, kg3 and SoG and is based solely on the test results of a sample of 317 timber joists comprising four species and all grown in the UK. For this sample, the adjusted r^2 value (from k-fold cross validation) is 0.91.

D.3 MoE OLS regression with single predictors

This sub-section reviews the performance of several models. Of interest is the identification of the good models, and then, what to do with the poorer ones: (i) adjust to ensure that they are conservative compared to the better ones or (ii) reject as unfit for purpose. A number of methods of adjustment are considered together with a star rating for models based on the range of their predictions (which can be used to differentiate between the useful and the rest). Tables are presented in Chapter 9 that summarise the models for MoE_{LCL} and MoR_{LCL} together with their star ratings. The discussions on the treatment of poorer predictive models apply to single-variate and multi-variate models for both MoE_{LCL} and MoR_{LCL} .

D.3.1 Adjustment of prediction equations

The relative power of the predictive equations for MoE_{LCL} can be seen to some degree graphically. The linear formulae above can be compared by converting the predictor variable values to a range of between 0 and 100 (i.e. a percentage scale). Additionally, as the slope of some lines are positive and some are negative, all values are adjusted to lead to positive slopes of the estimator line.

In Figure D.8 below, the measured MoE data points (in relation to three single predictor variables: MoE_{dyn}, SoG and kg3) and their linear estimates of MoE_{LCL} are shown. Only three variables are shown to prevent the graph being too cluttered to read. It is seen that the MoE_{dyn} linear estimate is steeply sloping, with a tight grouping of data points around it. This is clearly a better predictor than say, SoG (mentioned above), whose linear estimate is virtually level, with a diffuse spread of data points. It is seen that for predictor values of less than 35%, the SoG model gives higher values of MoE_{LCL}. This is inevitable due to the nature of regression modelling and the differences in the distributions of the two sets of data.

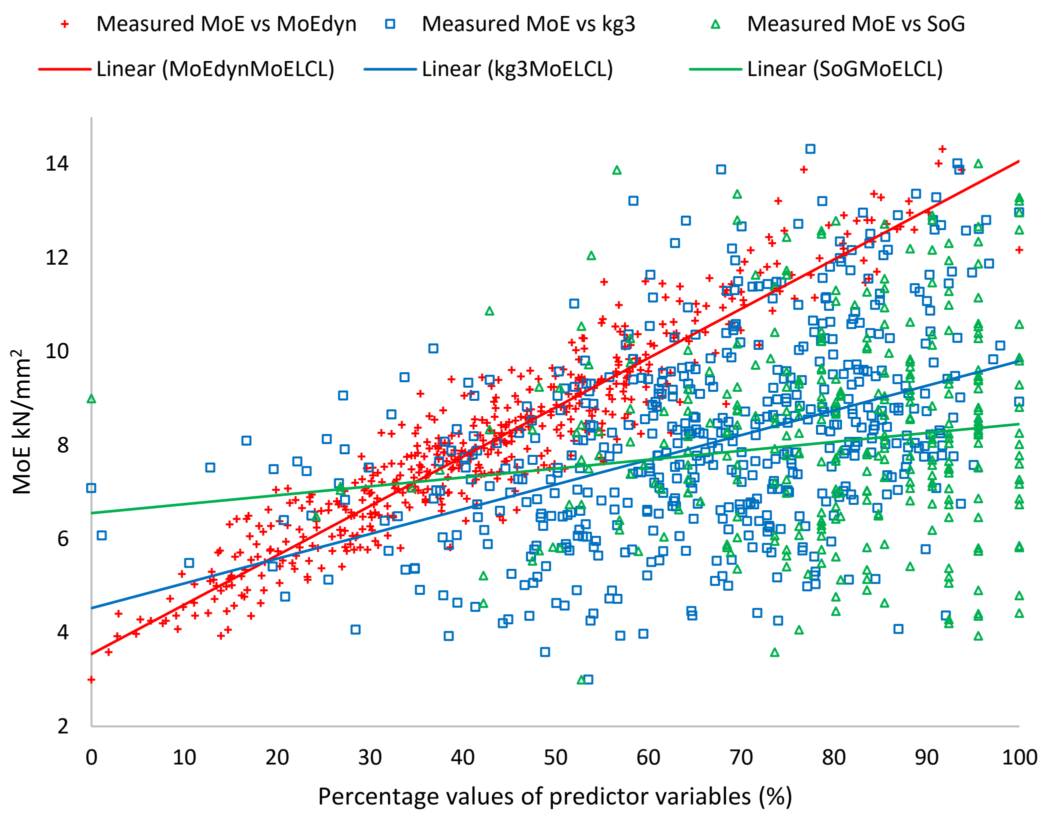

Figure D.8. Estimated MoE_{LCL} with normalised predictor variables also showing measured values of MoE

Similar graphs are presented in Figure D.9, with the data points removed and linear estimates included. Also included is a datum: normalised values of MoE are plotted along the x axis together with actual values of MoE along the y axis. This datum's perfectly linear arrangement of data points represents both the OLS regression line and its LCL (as there is no error in this model). The datum is shown in black and is seen to be very similar to the MoE_{dyn} LCL line. In this figure, it is seen that towards the left of the graph, the estimates of the weaker predictor variables are significantly higher than both the datum and the strongest single predictor of all, MoE_{dyn}. Therefore, consideration is given to penalise these high estimates.

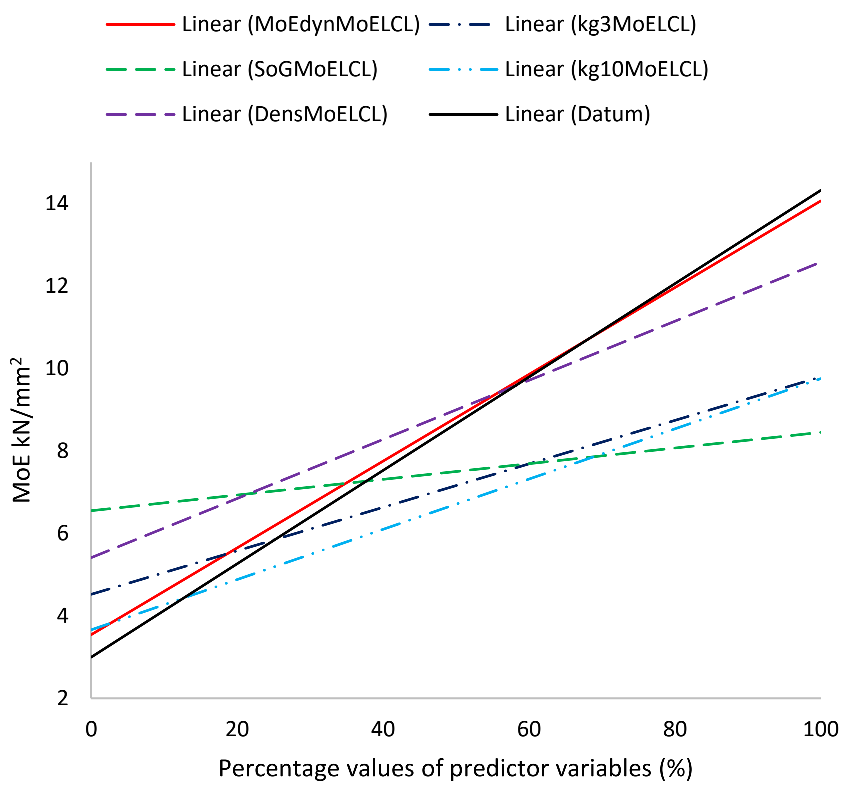

Figure D.9. Estimates of single predictors for MoELCL, also showing a datum and measured values of MoE

Several standard statistical techniques were considered and investigated, such as: (i) amend the 50% confidence interval to a greater width, (ii) use a prediction interval in place of the confidence interval, (iii) force the intercept of the graph to the origin or to some other datum point (and continue with a regression analysis through the scatter of data points), (iv) use a Model II regression analysis in place of the normal OLS analysis. None of these were considered to adequately deal with the issue.

The most common approach of forcing the intercept to the origin is inappropriate for two reasons. Firstly, for measures such as SoG and knot ratio measures, there is no zero point. MoE is expected to reduce as knot ratios increase and with the measure adopted, there is no maximum limit of say kg3 or kg10. This also holds true for SoG which approaches infinity as the grain angle approaches 90° to the longitudinal axis of the joists. Secondly, as values approach zero, they move further away from the actual material of wood and start to become a notional material which does not exist and about which we know nothing. So, even considering the MoE of wood when its density is supposedly say 10kg/m^3 makes no sense.

Therefore, some more unusual adjustment options were considered: firstly, adjust the slope of the linear estimates according to the size of the range of estimated values of MoE_{LCL}, as this range is directly related to the strength of the correlation between the predictor variable and MoE. Although this improved the linear estimates, it did not remove all of the high estimates. A second option to adjust the intercept of the linear estimates to limit the start of the graph (at zero % in Figure D.9, i.e. at the lowest measure in the data set) to no higher than a datum point was explored. However, keeping the slope of the graph the same (rather flat) led to the linear estimates being unreasonably conservative.

Thirdly and finally, an adjustment method using a new intercept based on a datum and keeping the highest point of the linear estimate was considered as being conservative without being overly punitive. Figure D.10 shows this for SoG. The datum used for the lowest point of the adjusted linear estimate is the lowest estimate of MoR_{LCL} using the best multivariate prediction model (3.247 kN/mm^2).

The nature of this datum is open to debate and this is settled upon as being a reasonable value. Additionally, the x-axis could be swapped from the normalised values of the predictor variable to say MoE and a slightly different set of adjusted equations would be created. The important thing is that several methods have been considered and a reasonable approach chosen that in turn can be refined or amended. This is a matter that can only be fully addressed once the issues of selection bias are adequately addressed. The adjusted linear estimates for several single predictors are shown in Figure D.11.

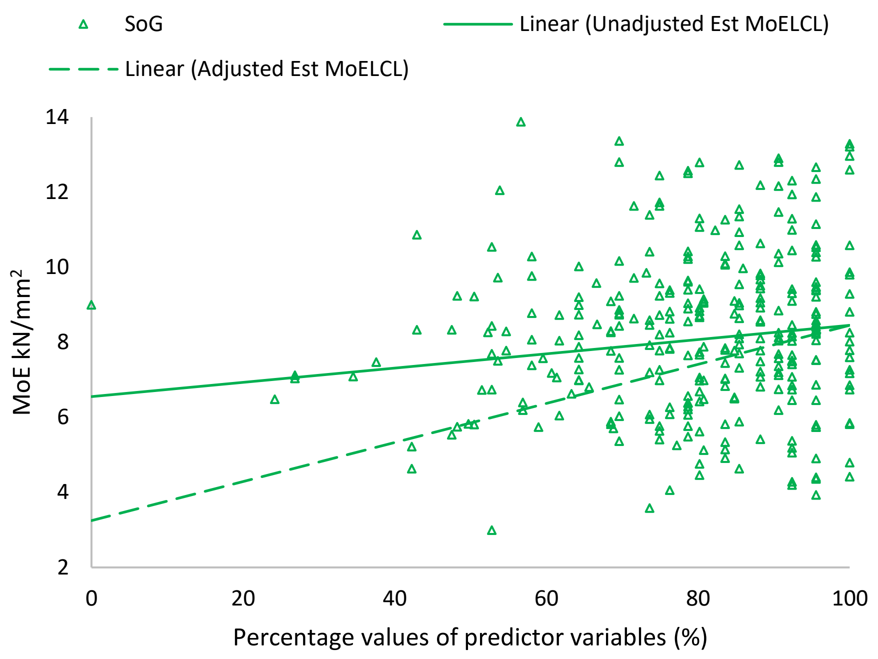

Figure D.10. Adjustment of the linear estimate for MoE_{LCL} based on SoG (the intercept of the adjusted estimate is 3.247 kN/mm^2)

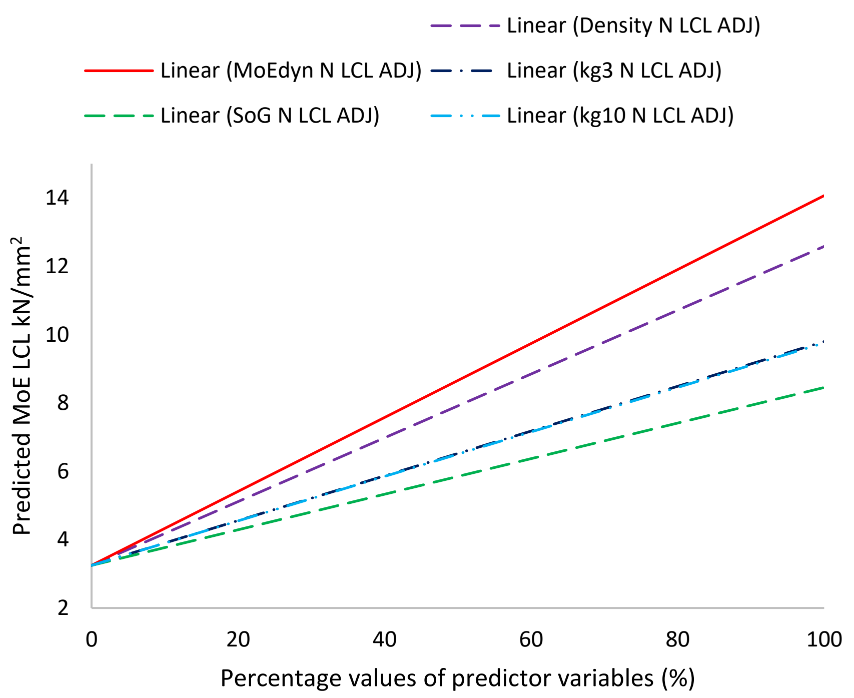

Figure D.11. Adjusted linear estimates for MoE_{LCL} for various predictor variables

While reading Figure D.11, it is worthwhile to consider typical characteristic values of MoE which may be used in current practice. From Chapter 4, it is noted that, using BS4978, the 527 joists are graded roughly into thirds (SS, GS and Reject) and that the characteristic values of MoE associated with these grades are 7 kN/mm^2, 9 kN/mm^2 and undefined stiffness. Additionally, the 50% two sided lower confidence limit of the mean of the whole minor species sample has a value of 8.1 kN/mm^2.

From the graph in Figure D.11, it is seen that MoE_{dyn} gives the highest predicted values and that density is also a useful predictor. For knot measures, the highest estimated values of MoE_{LCL} occur with zero knots (which relates to 100% on the percentage scale). By chance, this value is almost the same for both kg3 and kg10, therefore their adjusted linear estimates are almost the same also.

At this stage, each adjustment is based solely on the minor species data set and the linear estimates are expected to change as more data becomes available. Additionally, the method of the proposed adjustment is tentative as there are many possible variants which could be adopted. It is important to choose a final variant that is transparent, penalises the poor predictors (with low correlations) and is complementary to the Eurocodes.

Bearing in mind (i) the use of the characteristic value of MoE to predict deflections as part of serviceability limit state checks and (ii) the poor accuracy of characteristic values that are currently based on visual grading, then it could be argued to adopt no adjustment to the models and to simply use the MoE_{LCL} values obtained from them. However, firstly, it is noted that the possible over-deflection of floors in existing buildings is a common issue and one that is also borderline in many instances and so accurate estimates of stiffness are of value to structural engineers. Secondly, the weak performance of currently used methods is a poor reason to devise new methods that rely on weak predictors and that therefore over-estimate mean bending stiffnesses for some joists, without penalty.

At this stage, even though the predictive models based on single predictor variables (i) have been created in accordance with the Eurocodes, (ii) are clearly no worse than the current method of visually grading new timber and (iii) deformation of structures is rarely an ultimate limit state issue, it is still recommended that a penalty adjustment is used.

D.4 MoE OLS regression with multiple predictors

The 'best' model for MoE_{LCL} (MoE_{dyn} + kg3 + SoG) has an adjusted $r^2 = 0.912$. Three other models were developed to illustrate how multivariate models could be used and these have adjusted r^2 values of 0.897 (MoE_{dyn} + density) , 0.538 (kg3 + density) and 0.314 (kg3 + SoG). The strength of MoE_{dyn}, as a predictor, is clear from the drop in r^2 values when it is absent. Its effect can be seen in Figure D.12 on the range of predictions, the steepness of the slope of the trendlines and the grouping of data points around the trendlines. Figure D.12 shows the data points and trendlines of all four of the above predictive models on a single graph with MoE (as measured during testing) on the x axis.

Just as for the predictive models based on single variables, some of the models above are not conservative for MoE values below around 8 kN/mm^2. The poorer models are those that exclude MoE_{dyn}. The same discussion around penalizing the weaker single predictor models holds true for the weaker multivariate models too. Similar approaches are proposed which, while leading to conservative estimates of MoE, should prove acceptable to structural engineers.

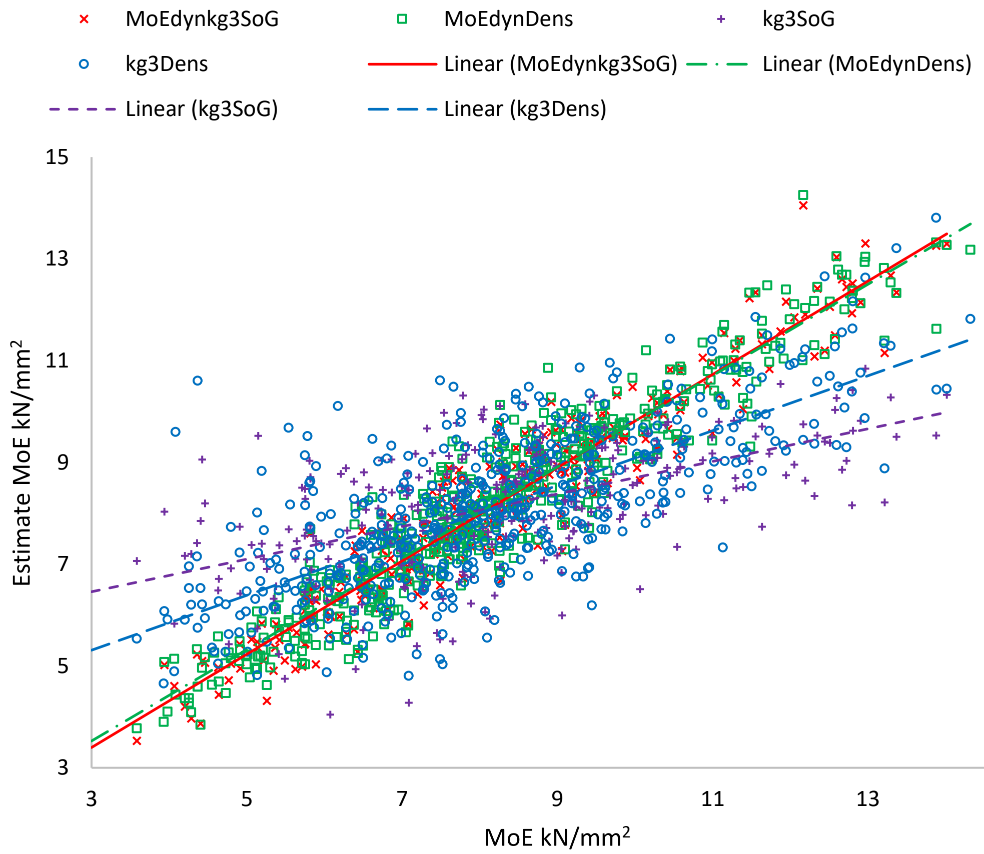

Figure D.12. Comparison of predictive models for MoE_{LCL} based on multiple predictors

The two multiple models containing MoE_{dyn} as a predictor need no adjustment (there is little difference between them and together, they are the best prediction models). The other two models containing kg3 require adjustment. This is more complex than for single variate models and requires some understanding of the 3D planar nature of the linear predictions. The process used for the predictive model based on kg3 and SoG is outlined below (the approach with the kg3 and density model is similar).

Four point estimates are calculated using the kg3 and SoG model for MoE_{LCL}, for the maximum and minimum values of SoG and kg3 measured in the minor species data set (n=317). These four point estimates are the four corners of a 3D predictive plane shown in Figure D.13. Next the size of the adjustment is calculated.

The minimum predicted value of MoE_{LCL} is obtained firstly using, the 'best' linear model and secondly, using the model in question based on the kg3 and SoG variables.

The difference between these two estimates is used as the 'adjustment value' by which the kg3 and SoG model is adjusted.

The 'adjustment value' is used to adjust down two of the estimates for MoE_{LCL} : (i) with kg3 set to a maximum (i.e. the worst case) and SoG set to a maximum also (this is the lowest corner of the predictive plane) and (ii) with kg3 set to a maximum and SoG set to a minimum. So, two corners of the predictive plane are lowered by the same amount. As SoG is by far the weaker of the two predictors, kg3 is chosen to be kept constant at its maximum, and then used with the maximum and minimum values of SoG. This approach can be refined by sharing the adjustment at not just two corners but at three corners (with values reduced in proportion to the importance of each variable in the model).

With four predicted values of MoE_{LCL} (two old and two new) which relate to the four positions of maximum and minimum kg3 and SoG, a new plane can be plotted and a new equation derived. This is the adjusted equation for MoE_{LCL} that includes a penalty and, in this case, the 'adjustment value' is 0.801 kN/mm^2.

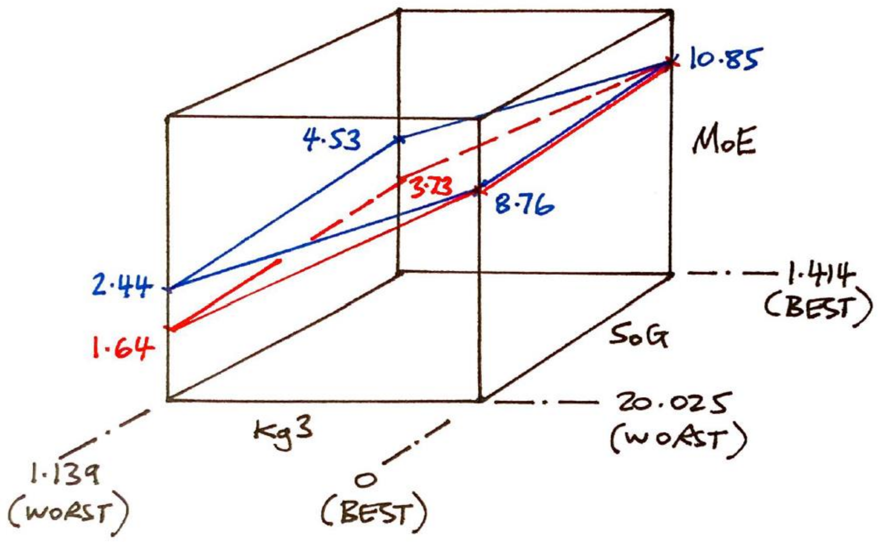

Figure D.13. Adjustment of the planar predictive equation for MoE_{LCL}

As for the single predictor variables, these adjusted models with multiple predictor variables are also checked from a different perspective(see Figure D.14). With observed values of MoE on the x-axis, it is seen that three of these models appear to work well but that the weakest of the four (SoG with the knot measure kg3) is still prone to over-prediction. This fourth model is given a two star rating in Chapter 9 and as such is not recommended for use in practice. The adjusted predictive models for MoE_{LCL} are given in Chapter 9.

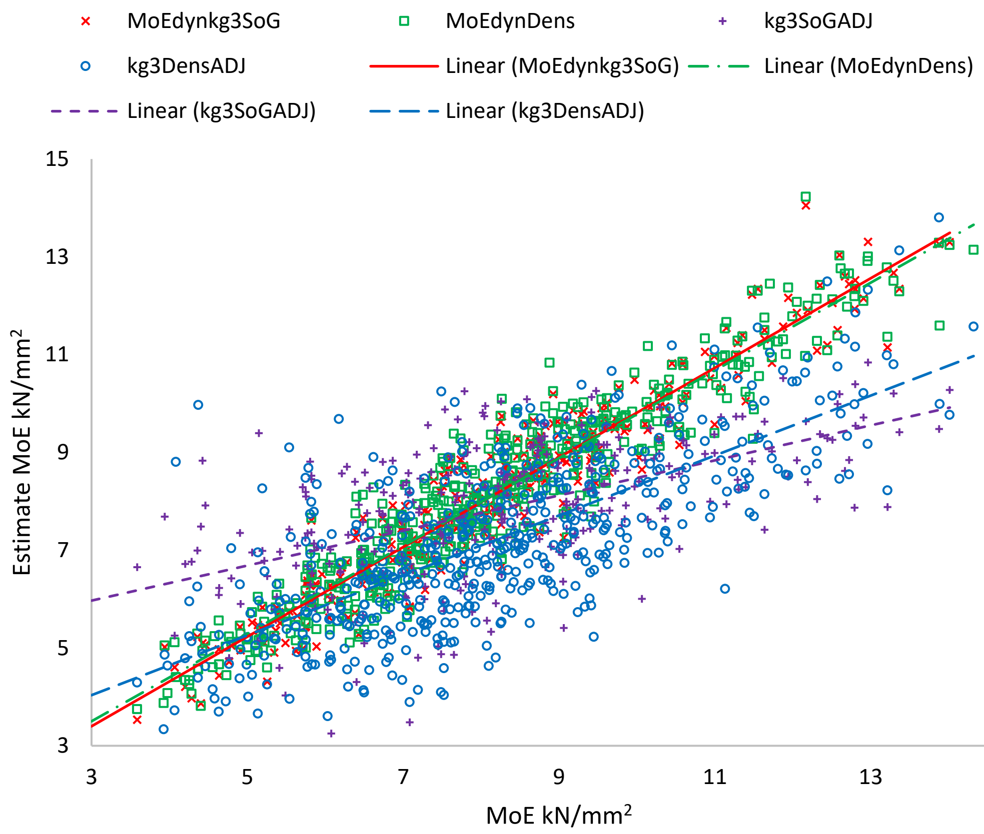

Figure D.14. Comparison of adjusted predictive models for MoE_{LCL} based on multiple predictors with measured MoE on the x-axis

Appendix E Further information on building the predictive model for the lower confidence limit of the 5 percentile value of density

E.1 Introduction

The purpose of this appendix is to supplement Chapter 8 by presenting more details of the model building process for the determination of the 50% two sided lower confidence limit of the 5 percentile (or 0.05 quantile, as it is generally referred to here) of density (termed density ρ_{LCL}) for individual joists. A brief discussion of the practicalities of using micro cores and DCE in the assessment of density in situ is also presented.

As part of the work of this thesis, a paper was written and presented at WCTE2016, the World Conference on Timber Engineering in Vienna, titled *'Combining of results from visual inspection, non-destructive testing and semi-destructive testing to predict the mechanical properties of western hemlock'* (Bather, Ridley-Ellis and Gil-Moreno, 2016). The conference paper includes fuller descriptions of materials and methodology, testing and results. What is presented here is just that which directly relates to density estimation.

Visual grading of 68 structural sized joists of western hemlock (*Tsuga heterophylla*) was carried out along with other NDT measurements, before testing to destruction in four point bending. Moisture content and density were then obtained. Two micro clear (6.5 mm diameter 91 mm long) specimens (A and B) were taken from undamaged regions of each tested joist and were measured and weighed. In short, it was found that in predicting properties of the structural sized joists, the averaged density from a pair of micro clear specimens was a good predictor of density. Thus, the model building focusses on the density obtained from the SDT measurements of these micro cores.

It is seen in the photograph how the two micro cores are located within a block of wood cut from the test piece (not the density block). The cores are aligned longitudinally as the principal purpose of the SDT measurements was to investigate parameters for the estimation of MoR (and not density). Reference to Figure E.1 shows how coring in this way can be seen to introduce additional variance due to the manner in which earlywood and latewood are included in the core.

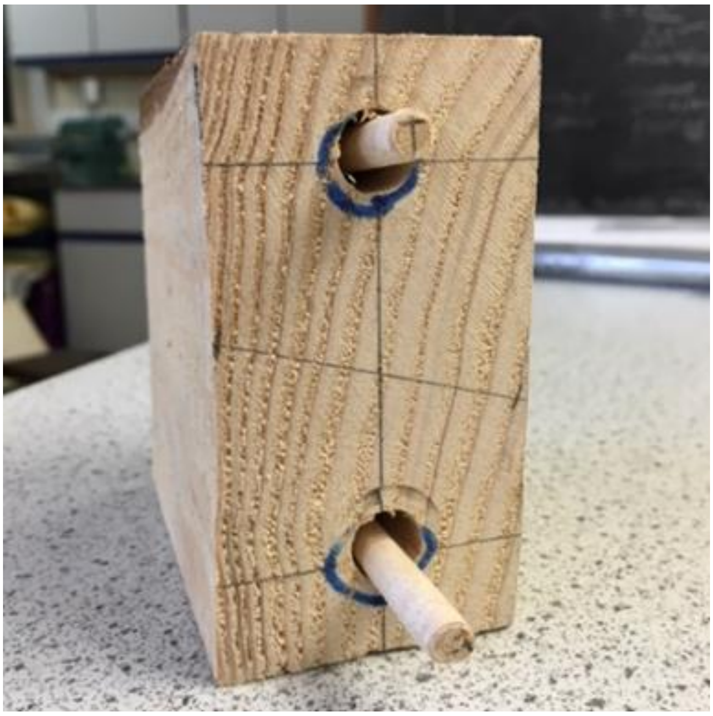

Figure E.1. Photo of two micro clear specimens cored from a block cut from a structural sized joist (specimens 'A' top, and 'B' bottom)

In place of sampling longitudinally, transverse sampling should ideally be carried out. Additionally, Martinez's study (2020) demonstrates that for a similar SDT method, there is no significant difference between sampling radially and tangentially. So, as long as one or other of these sampling directions could be adopted, it would be sufficient to prevent the dominance of either more dense latewood or less dense earlywood. In the field, taking two cores, at 90° to one another would be a sensible approach. Thus, it would be expected that, the variance in the predictive model considered in this thesis could easily be reduced in further studies.

The density of the structural sized joists is based on a 'block' cut from the joist in accordance with EN408 and adjusted for moisture content in accordance with EN384.

E.2 Model building

E.2.1 Predictor variables

Only two predictor variables are available for this study: micro clear density and RoG, which has in the past stood as a proxy for density. Previous studies show the weak correlation between RoG and density and this is borne out by the coefficient of determination $r^2 = 0.25$ found in this study. On this basis (and considering the difficulties of obtaining RoG measurements in situ), it is not proposed to make use of RoG in the predictive model.

E.2.2 Calculation of $\boldsymbol{\rho_{LCL}}$

The pros and cons of using quantile regression analysis to determine the 0.05 quantile is discussed in detail in Chapter 3 and in the appendices. This approach is combined with bootstrapping to determine the 50% two sided lower confidence limit of the 0.05 quantile of density ρ_{LCL} (from which, the 5 percentile characteristic value of density ρ_k can be determined).

Determining the equation for a 0.05 quantile is relatively straightforward, making use of the quantreg package in R, the predictive model for the 0.05 quantile of the density of an individual joist, based on the averaged density value of two micro cores is

$$
\begin{aligned}
&Est. 0.05\ quantile\ of\ density \\
&\qquad = 138 + 0.59\ \times Averaged\ micro\ clear\ density
\end{aligned}
\tag{E.1}
$$

Determining the equation for its two sided 50% lower confidence limit is a little more complicated and makes use of bootstrapping which is commonly used to generate confidence intervals without having to assume a particular distribution of a data set (Kabacoff, 2015). Bootstrapping is used to create a new data set through repeated uniform sampling with replacement from an existing data set such as the minor species one. The package boot and its function boot() enable bootstrapping to be carried out relatively easily using the statistical software R to create hundreds or thousands of notional bootstrapped data sets.

The linear estimate of the 0.05 quantile of density is based on the data set of block density results and averaged micro clear density results. For one given value of the averaged micro clear density (say, x_{new}) the intercept and slope of the linear estimate of the 0.05 quantile of density can be found, using the original data set. Together, these can be used to find an estimate of the 0.05 quantile of density for the particular value x_{new} . Next, for the same value (x_{new}) these coefficients can be found over and over again, say 1000 different times, using 1000 new notional data sets, obtained through the bootstrapping of the original data set. These coefficients can then be used together with x_{new} (which is held constant) to calculate 1000 estimates of the 0.05 quantile of density.

So, for the single value of x_{new} , its 1000 estimates of the 0.05 quantile have their own sampling distribution with a mean and confidence intervals around it. The R function boot.ci() operates on this sampling distribution to calculate the upper and lower bound confidence limits of the mean of the estimate. In this way, it is possible to determine the two sided 50% lower confidence limit for density, ρ_{LCL} , at x_{new} . Next, a range of values can be used in place of x_{new} (i.e. notional averaged micro clear density results) to calculate a range of values of the estimate of ρ_{LCL} which can be plotted onto a scatter plot. These calculated estimates can in turn be used to determine an equation for ρ_{LCL} based on the averaged micro clear density results.

A scatter plot with averaged micro clear densities on the horizontal axis and with block densities on the vertical axis is shown in Figure E.2. The lower confidence limit is calculated at ten separate, equally spaced points and at each of these points, the black crosses represent the estimates of the 0.05 quantile LCL value of density, ρ_{LCL} . The ten points can themselves be modelled (i) as a curve using a polynomial equation, (ii) a straight line using OLS regression or (iii) a straight line can be drawn from the outermost points which would form a conservative lower bound to the estimates.

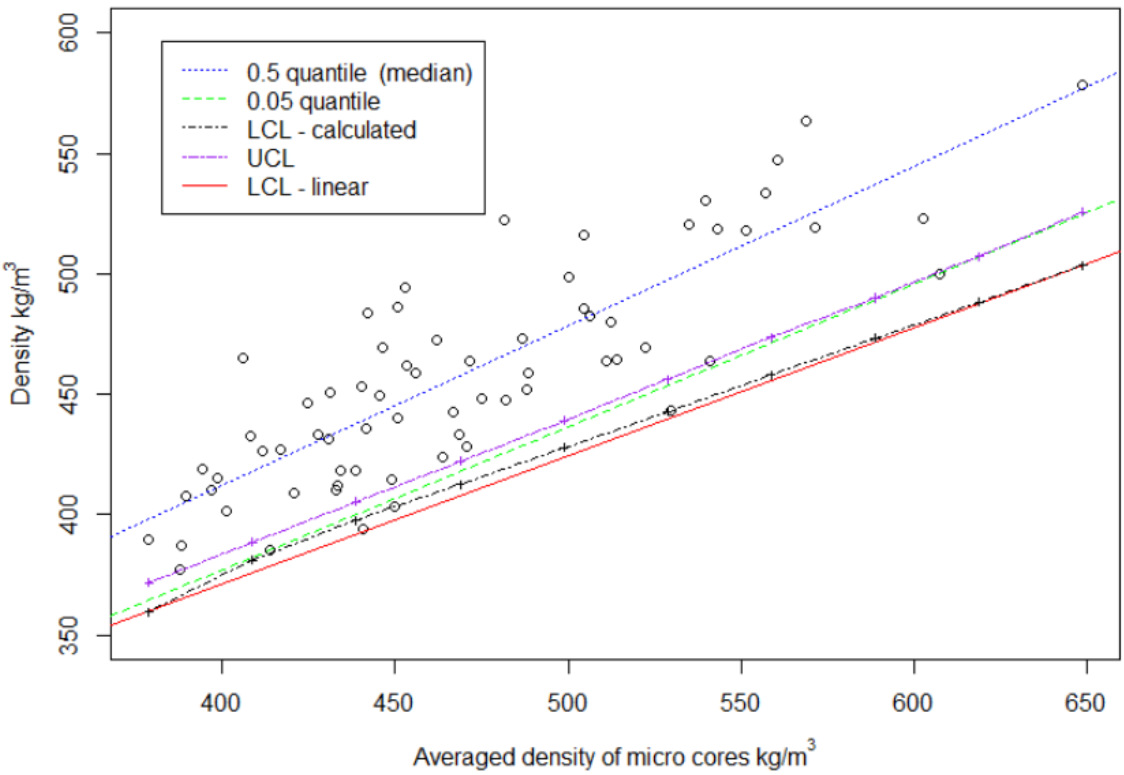

Figure E.2. Scatter plot of average of pairs of micro clear densities and 'block' density showing median, 0.05 quantile and its confidence limits

The curved line of the polynomial equation is the most complex approach which has a marginal increase in power over the linear equation based on OLS regression (r^2 = 0.999 compared to r^2 = 0.998). The complexity of the polynomial equation and its limited improvement over the linear equation make it unattractive. Due to the nature of OLS regression, around half of the slightly more accurate polynomial estimates will lie above and half will lie below the straight line (created using OLS regression). Hence, in order to comply with the Eurocodes and to demonstrate conservative outcomes, the third and simplest option is chosen, shown in red in Figure E.2. The greatest difference between the estimates of this conservative straight line and the polynomial curve is less than 6 kg/m^3. Figure E.3 shows in detail the polynomial and conservative lines and equations.

As timber is a complex subject which is poorly understood within the engineering community, it is considered good practice to reduce complexity wherever possible and so, at this stage, the conservative linear equation is proposed for the predictive model for density. The model therefore loses a little predictive power but is a little easier to use. As the data set, upon which the predictive models are based, expands, then this choice of the conservative lower bound line should be reviewed.

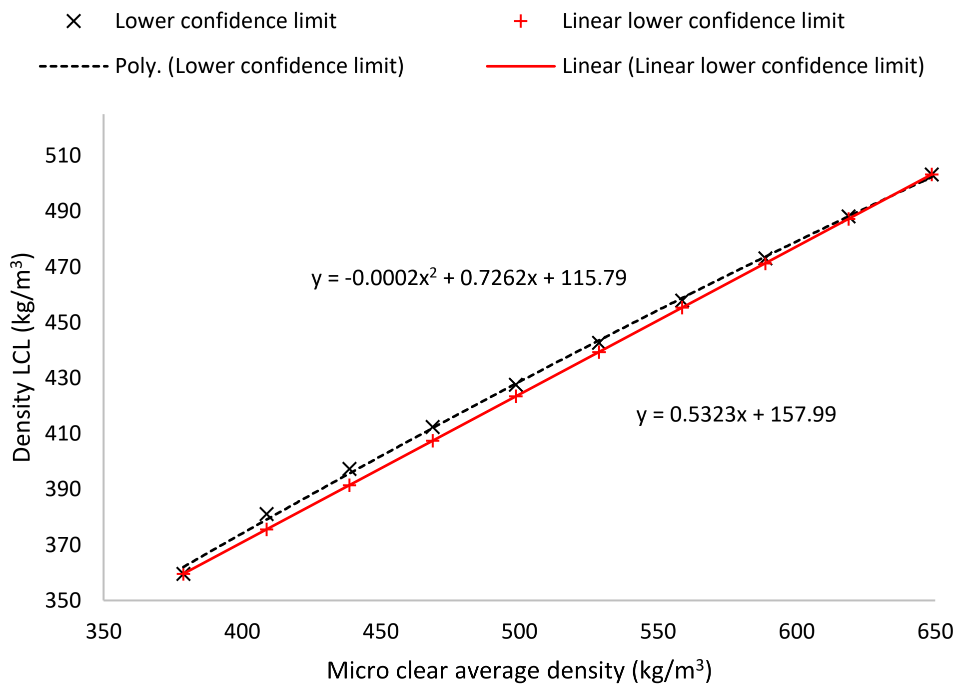

Figure E.3. Polynomial and linear models of the lower confidence limit for density

Regarding Figure E.2, it is worth noting that the data points are seen to gently funnel outwards from bottom left to top right and the 0.05 quantile is seen to diverge similarly from the 0.5 quantile (median). The distance of the lower confidence limit (LCL) from the 0.05 quantile also increases as density values increase towards the right of the graph. Towards the right hand side, there are fewer and more dispersed data points, indicating greater variance and so a wider confidence band is to be expected.

Next, a comparison is made between quantile and OLS regression coefficients using the plot() function from the quantreg package and the results are shown in Figure E.4; the upper graph is for the intercept and the lower one is for the slope. Almost the full range of quantiles (between 0.05 and 0.95) are shown on the x-axis. The values of the regression coefficients are shown on the y-axis. The horizontal red full line is the OLS regression coefficient which remains constant and does not vary across quantiles. The pair of horizontal red dashed lines are the upper and lower 95% limits of the confidence interval around the OLS regression coefficient. The black chain dotted line is the quantile regression coefficient which varies across quantiles. The grey band around the chain dotted line represents the confidence interval for the quantile regression coefficient. So, for instance, for the median (whose quantile is 0.5 and is similar to the mean), it is seen that the regression coefficients for both quantile and OLS regression are similar (around 150 for the intercept and around 0.65 for the slope); additionally the confidence bands around the coefficients for the median and mean are similarly wide. Apart from around the 0.90 quantile, none of the confidence intervals of the OLS or quantile regression coefficients encompass zero and so all three coefficients are significant.

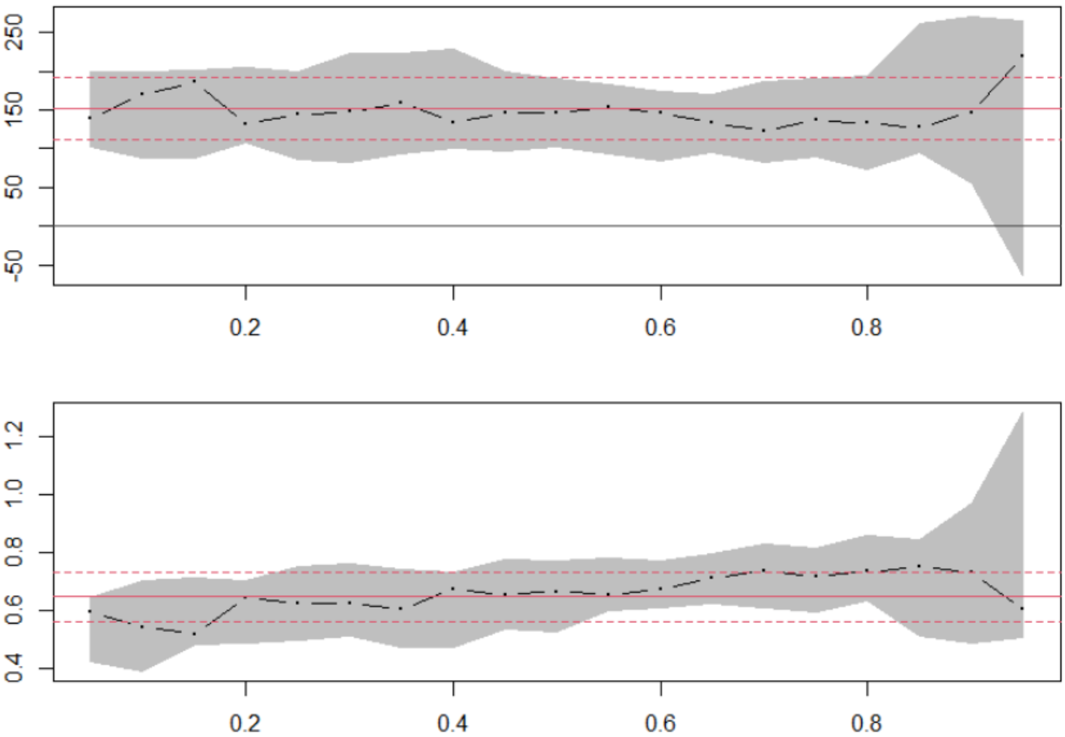

Figure E.4. Graphs showing the varying coefficients of the quantile regression models for density and the static OLS regression coefficients and associated confidence bands (upper graph for intercept and lower graph for slope)

A closer inspection of the graphs shows that, at the 0.05 quantile, both OLS and quantile estimates lie within each other's confidence bands. This shows that, from the limited data set considered, that there is not a significant difference between OLS and quantile regression in this instance. This is also the case at the 0.50 quantile (the median), which is similar to the mean.

Finally, the predictive model for the LCL density of a joist, based on the averaged density value of two cores is

$$Density_{LCL} = 158 + 0.53 \times Averaged\ micro\ clear\ density \quad \text{(E.2)}$$

E.3 Taking cores/samples from in situ timber

The removal of horizontal and vertical cores from in situ timber beams may significantly reduce their strength locally to resist shear and bending forces. For a simply supported beam supporting a uniformly distributed load, bending moments decrease from a maximum at midspan to zero at the supports and conversely shear forces decrease from a maximum at the supports to zero at midspan. It is important to locate the cores where their weakening effects on the timber beam are not critical, i.e. away from the high shear forces near the supports and the high bending moments at midspan.

From the old British Standard for timber design (BSI, 2002a), horizontal hole diameters at the neutral axis, not less than three diameters apart and whose diameter $d \leq 0.25 \times h\ (vertical\ height\ of\ beam)$, may safely be located between 0.25 and 0.4 of the span from each support.

From structural analysis calculations, vertical hole diameters are seen to have a greater weakening effect with regard to bending moments. Where the diameter of the core hole $d \leq 0.25 \times b\ (horizontal\ width)$, then they may be safely be located between 0.15 and 0.25 of the span from each support.

The above recommendations assume single core holes (not both horizontal and vertical together) and so a practical arrangement could be for horizontal cores located at 0.3 span from supports and spaced apart from vertical cores located at 0.2 span from supports. In practice, the number of cores and final locations would be a matter for the engineer surveying the structure (especially where support or loading differ from that described above).

As noted above, vertical cores significantly reduce the bending strength of beams and this effect can be ameliorated by using the drill chip extraction method (DCE) described in Sub-section 6.2.2.5. This has the benefit that the damage caused by DCE (8mm diameter holes 47.7mm long) is less than that caused by coring (12mm diameter holes, the full width or height of a timber element). This reduction in damage is particularly helpful when the timber element is borderline structurally adequate.

E.4 Use of DCE to model density

Both micro cores and DCE estimate density well. The chief benefit of micro cores is its robustness in use, a core is taken that can be examined and measured to obtain its density and it can be stored in the knowledge that it is a complete and sufficient sample. The chief benefit of DCE is the small size of its drill holes, whereas its chief disadvantage is it relies on 100% of drill chips and wood dust being trapped for analysis and it is hard to check this, so as equipment ages or operatives use the equipment incorrectly, errors can occur that are hard to spot. Nevertheless, DCE is worthy of further investigation thanks to the more limited damage it causes to in situ timber.

Figure E.5 shows the OLS regression line for the mean of the DCE observations and the densities of the specimens in the study by Martinez (2020, p. 6). The OLS regression line fits the five softwood species in the graph well and, working from the data in the journal article, there is a coefficient of determination of $r^2 = 0.97$ when plotting an OLS regression line through the mean values of DCE and specimen densities for the softwoods.

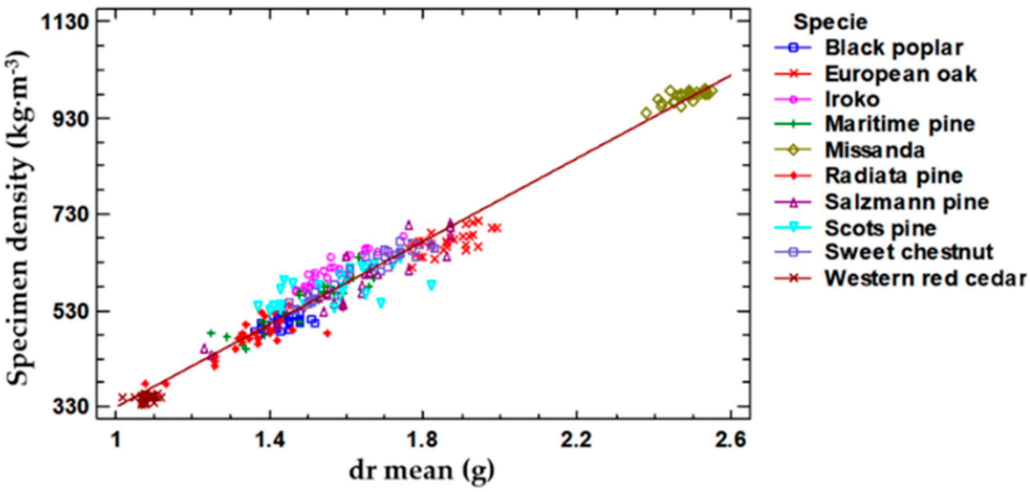

Figure E.5. DCE mean values plotted against values of specimens for density

Due to the reduced in situ damage of the DCE method combined with its proven efficacy, this is an attractive method to be used on site, especially as Martinez shows that good results can be obtained by drilling either radially or tangentially. However, for this thesis, there is sufficient data to build a preliminary model for the micro cores approach and not for the DCE approach. Another area of research lies here to extend the density model to estimate density by studying varying numbers of micro cores taken from specimens, studying the efficacy of micro cores on other species and making use of DCE to build another set of models, with one, two or more drillings per timber element.

Appendix F Further information on building the predictive model for the lower confidence limit of the 5 percentile value of MoR

F.1 Introduction

The purpose of this appendix is to supplement Chapter 8 by presenting more details of the model building process for the determination of the lower two sided 50% confidence limit of the 5 percentile (or 0.05 quantile, as it is generally referred to here) value of MoR (termed MoR_{LCL}) for individual joists. As for MoE_{LCL}, a range of predictive models are developed to align the thesis with the work of a practising engineer on site.

F.2 MoR quantile regression 'best' model building

The method chosen to build a model to predict the 0.05 quantile of MoR involves several stages which are similar to some of the stages followed for MoE (detailed in Appendix D).

OLS regression, which forms the basis of the predictive models for MoE_{LCL}, is a commonly used statistical technique that features in almost all elementary statistical textbooks and there is a wide range of statistical software programmes (and packages in R) that deal with each step of model building and analysis for OLS regression. This is not the case with quantile regression, which is a relatively new technique. Fortunately, in the statistical software programme R, there is a small number of packages that deal with quantile regression and the comparison of regression models. Thus, the method of quantile regression model building outlined below differs in several ways from the OLS method:

1. Use ANOVA to compare nested models and to understand the influence of each predictor variable considered
2. Compare models using the goodness of fit of the models
3. Compare quantile and OLS regression approaches to modelling the prediction of MoR, particularly in relation to heteroscedasticity

As quantile regression analysis is distribution free, there is no requirement to check a set of underlying assumptions as there is for OLS regression. When compared to an OLS regression model, the influence of outliers on a quantile regression model are generally assumed to be much smaller. So, due to the non-parametric approach adopted, no initial assessment of outliers is needed.

F.2.1 Predictor variables

Correlation between predictor variables and MoR are weaker than for MoE and density. Additionally, as is explained in Chapter 7, the relationships between the predictor variables and MoR vary by species. This short sub-section briefly outlines the choices made for the predictor variables.

As with MoE, reference should be made to Sub-section 5.3 which explains the method of selection of the knot measurement parameter kc3, in preference to the many other knot measurements available. Briefly, this is a measure of all knot diameters (accounting for overlapping knots) over a length of 300mm of a timber joist. The first choice of predictor variables is drawn from density, the dynamic modulus of elasticity (MoE_{dyn}), the knot group ratio kc3, the number of growth rings in a given length (RoG) and finally, slope of grain (SoG).

Reference should be made to Chapter 5, where the practicalities of measuring RoG and SoG in situ are discussed. It is concluded that due to the difficulties of measuring RoG in situ and the weakness of its predictive powers, it will not form part of a 'best' predictive model. Additionally, although the measurement of SoG requires the gouging of two or more shallow grooves in the surface of two or more faces of an existing in situ timber joist, this is a practicable operation and so SoG should be considered for the model (despite its known weakness as a predictor).

Finally, during the later consideration of the transformation of variables in this appendix, it is concluded that although the natural log of the knot measure kc3, lnkc3, is potentially a stronger predictor of MoR than the simple measure kc3, it should not be used. Therefore, although this variable and others such as RoG are considered in some of the model building analysis for completeness, they will not be part of the final 'best' model.

F.2.2 Relationships between the variables in the model

As the final 'best' model involves multiple regression, it is good practice to consider the relationships between the predictor variables two at a time. The principal diagonal in Figure F.1 shows the density and rug plots for each variable and it is seen that MoR has a double peak with a longer tail to the right indicating slight positive skewness. The left peak in the density plot is higher than the right peak and this distribution is also present (to varying degrees) in the density plots of all other variables excepting MoE_{dyn} and the knot measures. Both MoE_{dyn} and kc3 have broadly normal distributions and the natural log measure lnkc3 has a significantly longer tail to the left indicating negative skewness. The bivariate scatter plots show weak or moderate relationships between all variables. The scatter plots associated with MoE_{dyn} tend to show the strongest relationships with other variables.

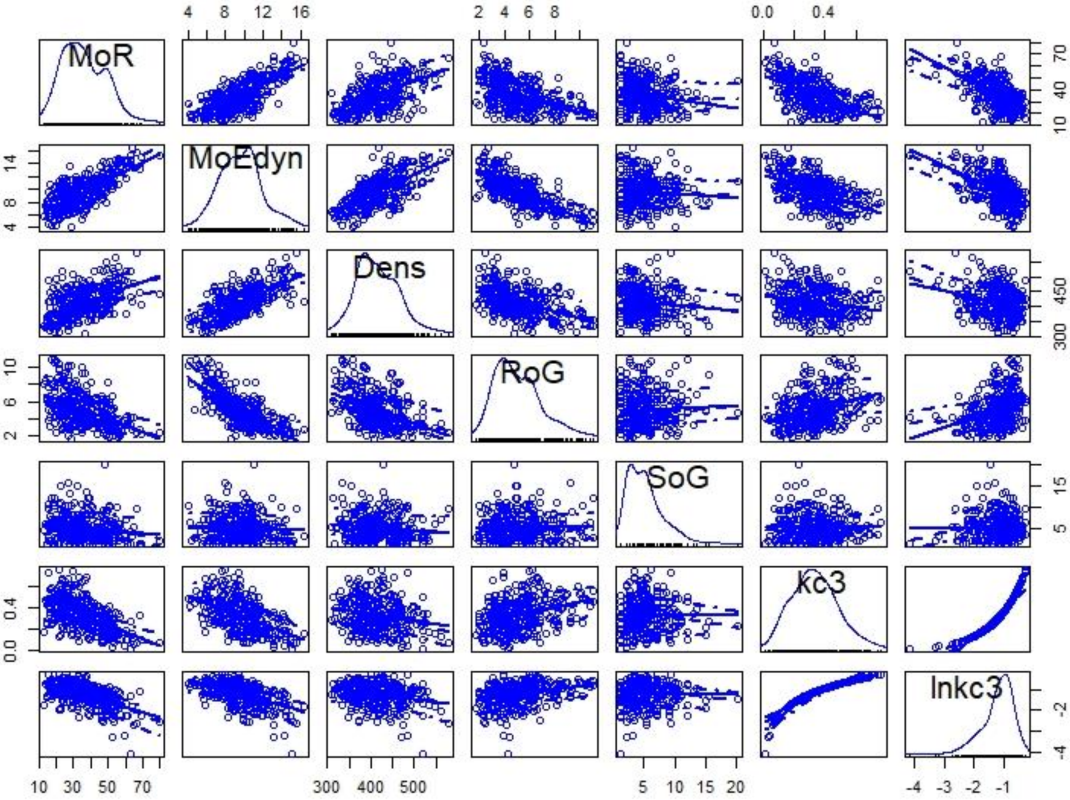

Figure F.1. Scatter plot matrix of dependent and predictor variables including linear and smoothed fits and marginal distributions (kernel-density plots and rug plots) (n=317, including all SoG and RoG results)

The double peaks of the MoR plot in Figure F.1 are further investigated. Figure F.2 shows the same phenomenon for two of the four species in the study. Both the western hemlock (WH) and the Norway spruce (NS) probability density graphs show a marked second peak to the right of the main peak. Figure F.3 shows the relative bending strengths of joists cut from different radial positions (R1 contains the pith and R5 is the outermost location of the trees with the largest diameters). The peak of the density plot of joists from position R5 lies to the right of the peaks of the density plots of the joists cut from other positions. Almost 90% of the R5 joists are either western hemlock or Norway spruce. This partially explains the second right hand peaks in the other graphs.

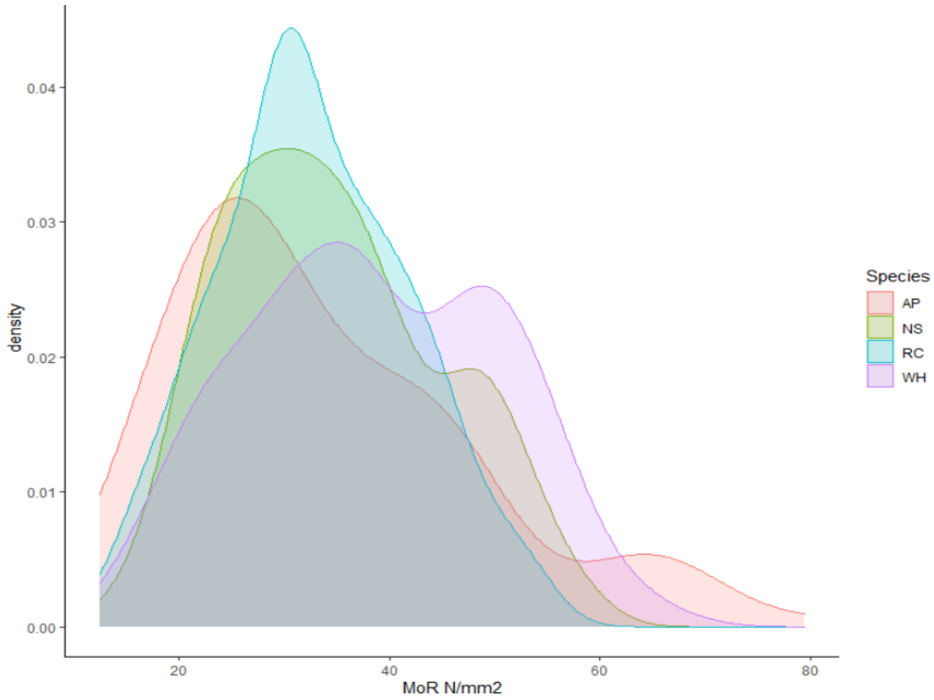

Figure F.2. Stacked density plots of MoR, differentiated by species

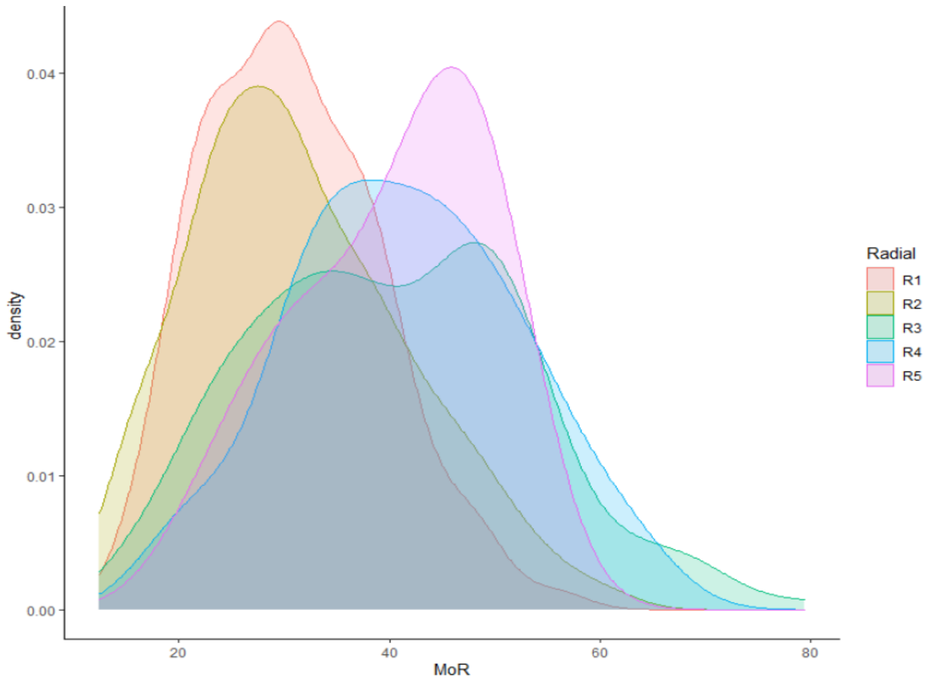

Figure F.3. Stacked density plots of MoR, differentiated by radial position

Having viewed the bivariate relationships graphically, it is now useful to consider the dependent variable with each predictor variable one at a time, as presented in Table F.1. These show MoE_{dyn} as the best individual predictor and SoG as the worst with density, knot measure and RoG in between.

Table F.1. Bivariate correlations between the predictor and dependent variables, two at a time (n=317)

	MoR	MoE_{dyn}	Dens	RoG	SoG	kc3	lnkc3
MoR	1	0.725	0.521	-0.488	-0.176	-0.562	-0.590
MoE_{dyn}	0.725	1	0.646	-0.729	-0.081	-0.513	-0.527
Dens	0.521	0.646	1	-0.454	-0.122	-0.206	-0.235
RoG	-0.488	-0.729	-0.454	1	0.050	0.339	0.323
SoG	-0.176	-0.081	-0.122	0.050	1	-0.007	0.021
kc3	-0.562	-0.513	-0.206	0.339	-0.007	1	0.933
lnkc3	-0.590	-0.527	-0.235	0.323	0.021	0.933	1

In Table F.1 it is seen that SoG and RoG correlate the least with MoR and so a second set of bivariate correlations have been obtained (this time using the full data set, excluding RoG and SoG) (n=527) and correlation coefficients are generally seen to be slightly reduced but with a similar pattern. The natural log of the knot measure is dropped from consideration due to the difficulties outlined in Sub-section F.3.4.

Table F.2. Bivariate correlations between the predictor and dependent variables, two at a time (n=527)

	MoR	MoE_{dyn}	Dens	kc3
MoR	1	0.700	0.499	-0.480
MoE_{dyn}	0.700	1	0.670	-0.356
Dens	0.499	0.670	1	-0.067
kc3	-0.480	-0.356	-0.067	1

From the correlation coefficients (based on OLS regression) the best predictors of mean MoR are MoE_{dyn}, density and kc3. Although RoG has a similar predictive power to density, it is not included in the proposed model firstly, as it has slightly less predictive power and secondly, due to difficulties of measuring RoG in situ. Finally, although SoG is seen to have a very weak correlation with MoR, it could potentially form part of a multivariate model.

F.2.3 Comparing nested models using ANOVA

The analysis of variance for fitted models can be calculated for both OLS and quantile regression. This can also be done for nested models which is useful in quantile regression model selection. An initial quantile regression model is created with a set of predictor variables. Then nested models (models whose terms are wholly included within the initial model) are also created and compared one by one with the initial model. The anova() function in R's base installation is used to test the usefulness of the predictor variables. Two test statistics are calculated and results are compiled into Table F.3.

The F value represents the ratio between the variation between groups and the variation within groups. Here, the groups comprise the predictor variables in the model building and so this can also be described as the variation in the model that is explained by the predictor variables divided by the unexplained variation. The null hypothesis in this test is that there is no variation between groups and for this to be so, we would expect the F value to be around 1; conversely values greater than 1 support the alternative hypothesis that there is significant variation between groups. The F value can be located within an F distribution, and larger F values indicate: (i) larger variation between groups when compared to the variation within groups (i.e. greater explanation of the variation in the model by the predictor variables), (ii) reducing probability that this is occurring by chance and (iii) greater likelihood that the alternative hypothesis (of significant variation between groups) holds. Thus, p-values lower than say 0.05 are taken to confirm significant variation between groups.

Where a nested model is not significantly different to the initial model then a high p-value is returned and the predictor variable that differentiated between the two models can be considered to be dropped from the model. Where a significant difference is indicated (by a low p-value) then the predictor variable that differentiates between the models should be considered to be kept.

Six sets of nested models were tested in a step by step way using the ANOVA analysis and the results, of the three models excluding RoG, are presented in Table F.3. The shaded cells are the worst performing predictor variables.

Table F.3. Results of nested ANOVA analyses for quantile regression predictor variables for MoR (0.05 quantile only) (including MoE_{dyn}). Cells shaded grey with higher p-values and lower F values

Predictors omitted	F value	p-value
1. Initial model: MoE_{dyn} + kc3 + Dens + SoG (n=317)		
SoG	1.144	0.286
Dens	1.300	0.255
kc3	6.437	0.012
MoE_{dyn}	5.119	0.024
2. Initial model: MoE_{dyn} + kc3 + Dens (n=317)		
Dens	0.411	0.522
kc3	6.917	0.009
MoE_{dyn}	22.049	3.982×10^{-6}
3. Initial model: MoE_{dyn} + kc3 + Dens (n=527)		
Dens	0.528	0.468
kc3	27.384	2.419×10^{-7}
MoE_{dyn}	33.871	1.027×10^{-8}

The first initial ANOVA analysis includes all possible predictor variables (excluding RoG) and suggests that the most important of these are MoE_{dyn} and kc3. Density and SoG variables could be dropped, one by one, and not significantly affect the initial quantile regression model. In the second and third analyses, SoG is omitted and density is shown to be a weak influence.

The results of these ANOVA analyses show that SoG and density can be dropped from the 'best' quantile regression model without significantly affecting its performance. The F values returned by the anova() function fit well with the probability levels reported. Typically, much higher F values are calculated for those predictor variables that have a significant effect on the regression model: MoE_{dyn} and kc3.

From the nested ANOVA analyses, the 'best' set of predictor variables for the 0.05 quantile regression model include just MoE_{dyn} and kc3. This is a good start for the 'best' model building. However, on occasion it may not be practicable to measure MoE_{dyn} and so a reduced model is also considered to illustrate how other models could be created.

Table F.4. Results of nested ANOVA analyses for quantile regression predictor variables for MoR (0.05 quantile only) (excluding MoE_{dyn})). Cells shaded grey with higher p-values and lower F values

Predictors omitted	F value	p-value
Initial model: kc3 + Dens + SoG (n=317)		
SoG	0.951	0.330
Dens	10.629	0.001
kc3	12.979	3.663×10^{-3}

The values in Table F.4 show the weakness of the SoG predictor and the strength of the knot measure kc3 and density. Therefore, models without MoE_{dyn} could best be based on kc3 and density.

F.2.4 Comparison of AIC values

The vest.lqr() function of the R package lqr is used to calculate the AIC values for a variety of models using different numbers of predictor variables. Once again RoG is excluded from consideration. Table F.5 shows that a group of three models have very similar AIC values and as such all three could be considered further.

Table F.5. AIC values for the 0.05 quantile models with varying numbers of predictor variables (n = sample size, p = number of predictor variables). Green shaded cells indicate models with similarly low AIC values

Predictor variables	n	p	AIC
MoE_{dyn} + kc3 + SoG + Dens	317	4	2814
MoE_{dyn} + kc3 + SoG	317	3	2816
MoE_{dyn} + kc3	317	2	2815
MoE_{dyn} + Dens	317	2	2853
MoE_{dyn} + SoG	317	2	2852
MoE_{dyn}	317	1	2852
MoE_{dyn}+ kc3	527	2	4701
MoE_{dyn}	527	1	4719

Based on the nested ANOVA and AIC results, it is concluded that the best set of predictor variables for the 0.05 quantile regression model include just MoE_{dyn} and kc3. Although the AIC values suggest that the model should include MoE_{dyn} and kc3, they are not particularly helpful at clarifying the usefulness of adding more variables to the model.

F.2.5 Transformation of variables

The earlier assessment of knot ratios discussed in Chapter 5, is based on OLS regression and different transformations of the knot ratio measures were compared using their coefficients of determination, r^2. While this is not directly relevant to the transformation of predictor variables in a quantile regression, this gives some indication. The tentative conclusion of these earlier comparisons, combined with the discussions in the previous sub-section, is that no transformation of knot ratio measure should be used.

Now, directly considering 0.05 quantile regression models for MoR, three methods are used to consider the possible transformation of the knot ratio measure: goodness of fit tests, ANOVA and the Akaike information criterion.

Using the goodness of fit test in the GOFTest() in the QTools package, two 0.05 quantile regression models to predict MoR are compared (He and Zhu, 2003). The first model comprises MoE_{dyn} and the simple knot ratio measure kc3. The second model replaces the simple knot ratio with a transformation of the knot ratio. In the analyses presented below for the knot ratio, the only transformation considered is the squared knot ratio, as from Chapter 5, this is the best transformation (after the natural log).

The first model has a goodness of fit statistic of 0.0317 and a p-value of 0.014 (n=317). This compares with the second model's statistic of 0.0078 and p-value of 0.442 (n=317). As a large test statistic and small p-value is evidence of lack of fit, then the model to be preferred is the one using the squared knot ratio.

This was further investigated by creating an initial 0.05 quantile regression model to predict MoR with MoE_{dyn} and both the simple knot ratio and its square. Two nested models were created by dropping firstly just the squared knot ratio and secondly just the simple knot ratio. These nested models were subsequently compared with the initial model using ANOVA.

Dropping the simple knot ratio in the second model leads to a slightly higher F value and lower p-value than dropping its square. This indicates that the first model is less different to the initial model than the second and so the squared knot ratio should be dropped from the model. Although this is the opposite conclusion to the GOFTest, the values of the F test and p-value for the two models are similar, suggesting that the conclusion is not a strong one.

From the lqr R package, the function best.lqr() calculates the Akaike information criterion (and other similar statistics: the Bayes information criterion (BIC) and the Hannan-Quin information criterion (HQ)) and also produces graphs to assist in the selection of the most appropriate predictor variables. This package was used to compare two 0.05 quantile regression models using MoE_{dyn} to predict MoR; the first includes only the simple knot ratio and the second includes only the squared knot ratio. The Akaike information criterion (AIC) was calculated for each of the two models using five different distributions. Based on the student's t distribution, AIC values for the two models are almost the same (2378 for model 1 and 2388 for model 2). This result favours the simple knot ratio by a small degree.

In summary, for the MoR 0.05 quantile regression model, two tests out of three favour the inclusion of the simple knot ratio over the squared knot ratio and all tests indicate that there is little to choose between the two predictor variables. On the basis of these results it is concluded that no transformation of the knot ratio should be included in the 0.05 quantile regression model and that the simple knot ratio should be used. This accords well with the results of similar comparisons based on OLS regression models and the literature review.

The same three methods are used to consider the possible transformation of the MoE_{dyn} predictor variable: goodness of fit tests, ANOVA and the Akaike information criterion. As the knot measure could be equal to zero neither its natural log nor its reciprocal could be used as transformed measures. However, as MoE_{dyn} is never equal to zero, some additional transformations need to be considered.

Once again, the outcome of the tests for transformation of the predictor variable is not clear cut. The goodness of fit tests indicate that the reciprocal of MoE_{dyn} and the reciprocal of MoE_{dyn} squared do not improve upon simply using the predictor MoE_{dyn}. Conversely, the goodness of fit tests indicate that the natural log is marginally a better predictor than simply using the predictor MoE_{dyn}. The value of using the square of MoE_{dyn} differs according to the sample size (n=317 and n=527): worse with the small sample and better with the large one. The ANOVA analysis indicates that the square of MoE_{dyn} is an improvement but that the natural log is not. Finally, the AIC statistics in Table F.6 indicate that only the square of MoE_{dyn}, which has the lowest AIC value of all, is an improvement over simply using the predictor MoE_{dyn}.

Table F.6. AIC values for the 0.05 quantile regression model for MoR and including kc3 and MoE_{dyn}

Transformation	AIC
$MoEdyn$	3953
$MoEdyn^2$	3941
$1/MoEdyn$	3977
$1/MoEdyn^2$	3990
$\ln MoEdyn$	3964

Bearing in mind the marginal and contradictory differences indicated in the results of the calculations, it is concluded that the predictor variable MoE_{dyn} should be used without transformation. The same conclusion is also applied to the variables SoG and density, namely no transformation should be applied.

F.2.6 0.05 quantile regression model

An explanation and discussion of quantile regression is given in Chapter 3 and its application to building a model with a single variable is described in relation to density, where a method for determining the 50% two sided lower confidence limit (LCL) is also described in Appendix E. For the 'best' model for the 0.05 quantile of MoR and for MoR_{LCL}, similar techniques are applied but with a slight difference for determination of LCL for the multivariate 'best' model in place of the single variate model (used with density).

First, the equation for the 0.05 quantile is determined and the predictive model for the 0.05 quantile of the MoR of an individual joist, based on MoE_{dyn} and the knot measure kc3 and using the full data set (n=527) is

$$Estimated\ 0.05\ quantile\ MoR = 9.301 + 1.799\ MoEdyn - 14.383\ kc3 \quad \text{(F.1)}$$

This is found using the quantreg package in R and checked using the k-fold cross validation function cv.rq.pen() from the package rqPen, also in R (which gives similar but slightly different coefficients). Also, based on the reduced data set (n=317), the following model is derived, whose coefficients lie within the confidence band of the full model (n=527) but clearly differ

$$Estimated\ 0.05\ quantile\ MoR = 3.943 + 2.215\ MoEdyn - 12.527\ kc3 \quad \text{(F.2)}$$

The differences between these models suggest that care should be taken not to over fit a predictive model as it is likely to change as new data is acquired and introduced into the model.

The Breusch Pagan test for heteroscedasticity was carried out by fitting a linear regression model to the residuals of a regression model. From the lmtest package in R, the function bptest() performs this and the results indicate significant heteroscedasticity showing the appropriateness of using quantile regression and the inappropriateness of using OLS regression. This is illustrated in Figure F.4, where a comparison is made between quantile and OLS regression coefficients in a similar way to the comparison made for density (an explanation of the lines and shading is give in Appendix E). None of the confidence intervals of the OLS or quantile regression coefficients encompass zero and so all three coefficients are significant.

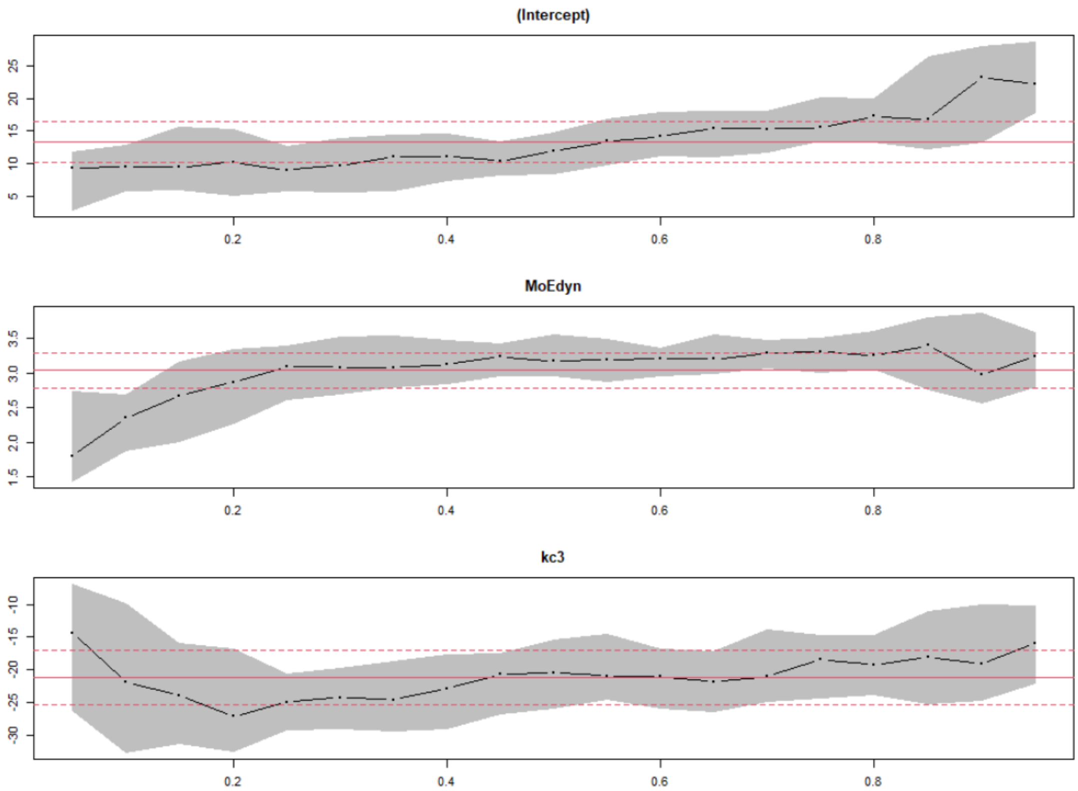

Figure F.4. Graphs showing the varying coefficients of the quantile regression models for MoR (between 0.05 and 0.95 quantiles) and the static OLS regression coefficients and associated confidence bands

Figure F.4 shows the full range of quantile regression coefficients from 0.05 to 0.95. These generally lie within the confidence limits of the OLS regression coefficients, and for the 0.50 quantile (the median) are very similar; however, significant differences are apparent at each end of the ranges. A separate ANOVA analysis also shows that the models for the 0.05 to 0.95 quantiles are significantly different. So, a closer investigation of the zone around the 0.05 quantile is merited and is provided in Figure F.5.

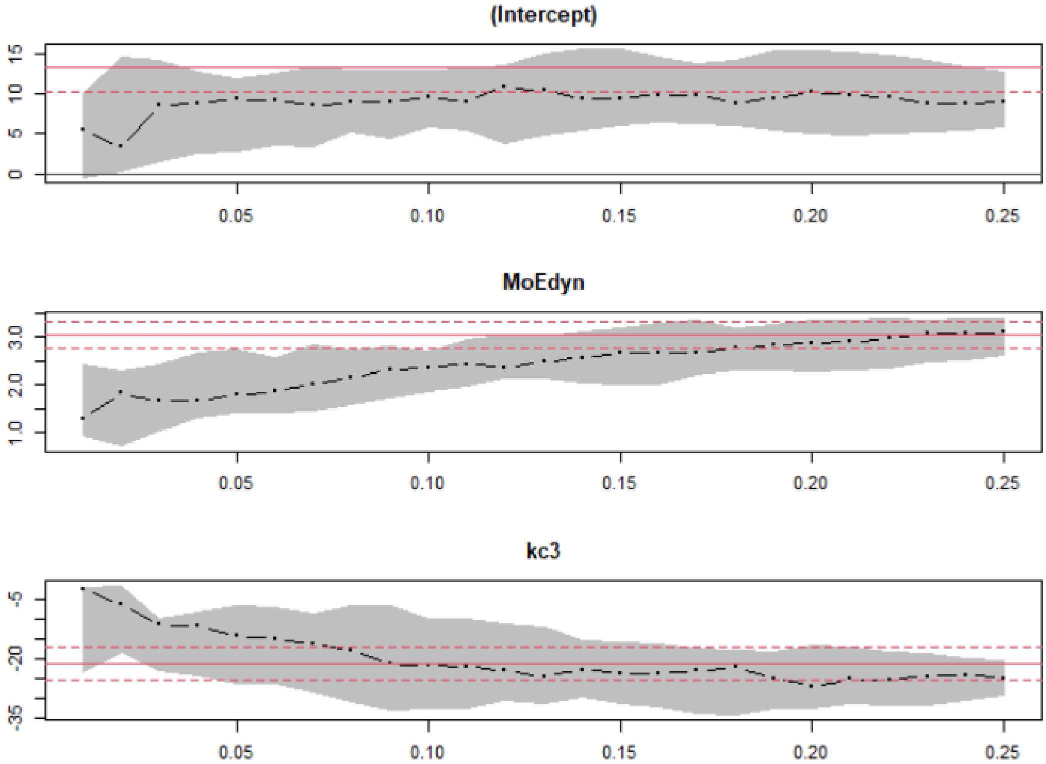

Figure F.5. Graphs showing the varying coefficients of the quantile regression models for MoR (between 0.01 and 0.25 quantiles) and the static OLS regression coefficients and associated confidence bands

All three quantile regression coefficients at the 0.05 quantile lie outside the confidence limits of the OLS regression model, and for MoE_{dyn}, there is no overlap of the confidence bands of the two regression models. This shows a significant difference between the two models and as argued previously, the quantile regression model is considered to be more appropriate than the OLS model.

F.2.7 The predictive equation

As per EN14358, the characteristic value of MoR is the lower confidence limit or bound of a two sided 50% confidence interval and for MoR, this is termed MoR_{LCL}. The use of quantile regression analysis followed by bootstrapping to determine confidence intervals for a single predictor variable is explained and discussed in Chapter 3 and in relation to density. For MoR, two predictor variables are proposed for the 'best' model and so a slightly different approach to the bootstrapping for the creation of the model to estimate MoR_{LCL} is needed. The predictive equation for MoR_{LCL} is subsequently used to determine the 5 percentile characteristic value of bending strength $f_{m.k}$.

As the predictive equation for MoR_{LCL} has two untransformed predictor variables, it can be represented by a plane whose location and slopes are determined by the intercept and the two coefficients for MoE_{dyn} and kc3 respectively. Therefore a range of bootstrapped LCL values are calculated to define the outer edges of the plane which are located at the extreme ends of the ranges of density and kc3 values. Additionally, from the predictive model for the 0.05 quantile of MoR, it is seen that density is of greater importance to the model than the knot measure kc3. Thus, the number of LCL values calculated are weighted in favour of density. So, for the predictive equation for MoR_{LCL} a total of 30 bootstrapped LCL values are used (20 of density and 10 of kc3).

In order to be sure of this approach, several models were created using different numbers of bootstrapped LCL values representing both predictor variables in different ratios. From this exploratory work, it is seen that the number and range of values used is sufficient and that using a greater number of values would not significantly affect any models generated from this data.

The 'best' predictive equation for MoR_{LCL} generated the way described above is

$$MoR_{LCL} = 8.07 + 1.78\ MoEdyn - 14.25\ kc3 \tag{F.3}$$

When this is used to calculate MoR_{LCL} values for the individual joists in the minor species data set, the range of these values is 26.7 N/mm^2. They are represented graphically in Figure F.6 which shows the steep slope of the plane relative to MoE_{dyn} and the relatively shallow slope of the plane relative to kc3.

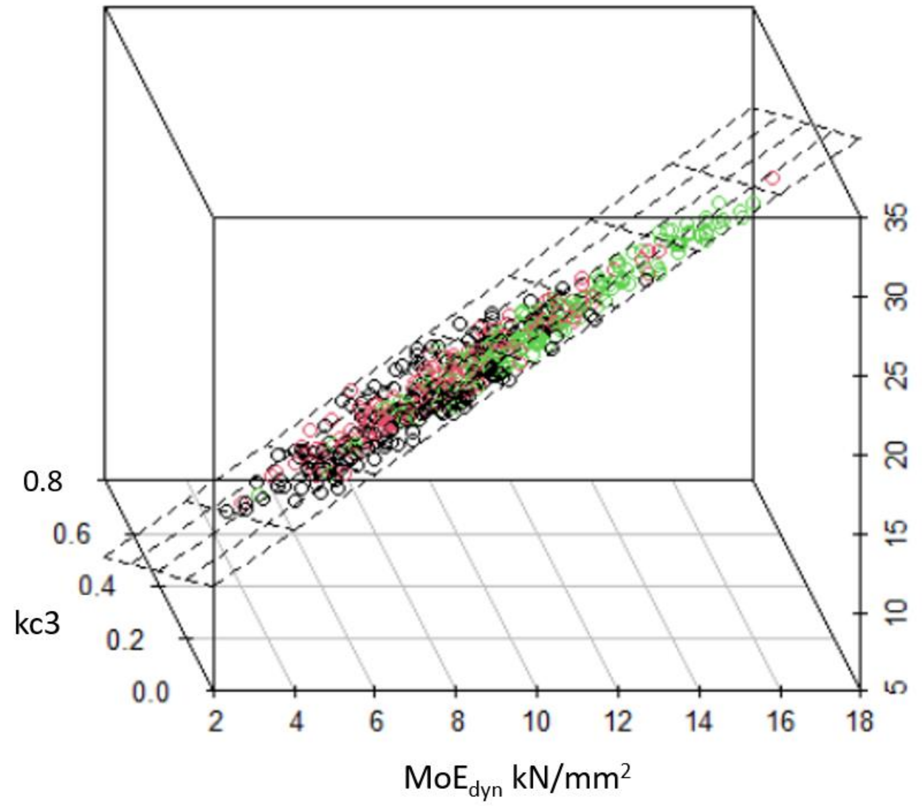

Figure F.6. 3D graph of MoR_{LCL} as predicted using MoE_{dyn} and kc3

F.2.8 Modelling straight and curved lines (MoE, density and MoR)

In the model building of this thesis, choices have had to be made whether to use straight or curved line models for mean MoE, 0.05 quantile density and MoR, and their 50% two sided lower confidence limits (LCL). For MoE, the correlation between MoE_{dyn} and MoE is so strong, that a linear model for both mean and LCL is chosen, as the mean is considered to approximate well to a straight line and although it is known that the LCL is curved, the values of LCL are so close to those of the mean that differences between straight and curved line models are negligible.

For the predictive model of the 0.05 quantile of density, quantile regression used in this thesis yields a straight line. In the future, with a larger data set, it would be useful to see if a curved line fits the data significantly better. The principles of quantile regression could form the basis of the creation of a curved line model. For density, the LCL is based on a single predictor variable and is known to curve and so could be modelled as such. Bearing in mind the limited data set upon which the modelling is based: (i) a linear model is chosen to reduce complexity and (ii) a conservative one is chosen to clearly demonstrate an acceptable approach in relation to the Eurocodes. This is despite there being a case to create either a curved model (to more closely match the estimates of density LCL obtained through bootstrapping) or a straight line model based on OLS regression through the estimates (less conservative than the chosen model, but more accurate).

The choices in the modelling of MoR_{LCL} are made in a similar way to the choices for density, but due to there being multiple predictor variables, firstly it is harder to picture and secondly it is harder to model. In this thesis, the conservative straight line approach is adopted for the same reasons that it is adopted for density.

The upshot of all this is that future research (especially with an expanded data set) should revisit these decisions regarding straight and curved line models, balancing accuracy, compliance with the Eurocodes and complexity. For reasons discussed in Chapter 7 it is too early to consider this matter further at present.

F.3 MoR quantile regression with single predictors

This sub-section considers some of the issues relating to the predictor variables used in the model building for MoR_{LCL} : namely the differences between species and the differences in power and effect of the different variables. Some discussion of penalising the weaker predictive models is followed by further discussion on the exclusion of the natural log of the knot measure kc3 in any predictive model.

F.3.1 Predictions of the 0.05 quantile of MoR varying by species

The estimate of the 0.05 quantile of MoR relies on its correlations with its predictor variables and these are expected to vary by species. MoE_{dyn} is the strongest predictor and so it is worthwhile comparing the relationships between MoE_{dyn} and the 0.05 quantile of MoR for specific species and for all species together. Figure F.7 shows the 0.05 quantile regression lines.

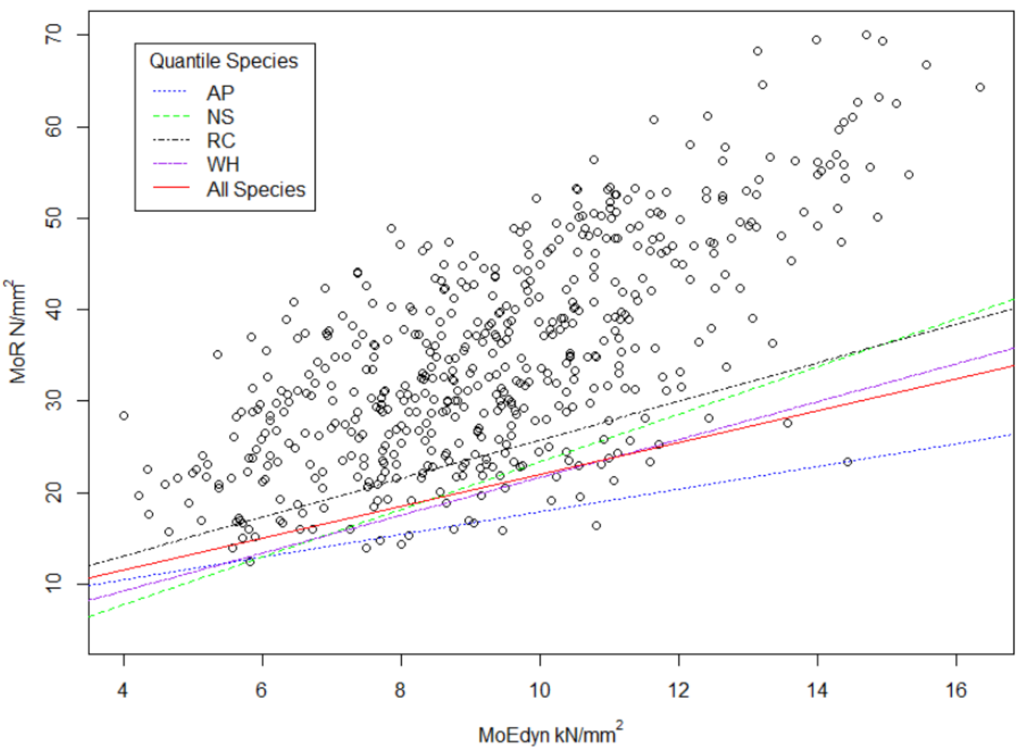

Figure F.7. 0.05 quantile plots of MoE_{dyn} and MoR for four specific species and all species together

In Figure F.7, as is to be expected, the solid red line (0.05 quantile) for all species lies approximately in the middle of the other four lines (0.05 quantiles). Bearing in mind that the 50% two sided confidence band around the solid red line for all species varies between approximately 1 and 3 N/mm^2, then it is clear that the 0.05 quantile lines of some species lie outside the two sided 50% confidence band of the quantile line for all species. This is an inevitable outcome of adopting a species-free approach for the predictive model. Reference should be made to Chapter 7 for further discussion on this.

It is worthwhile viewing a graph for kc3, similar to that for MoE_{dyn} and Figure F.8 shows the 0.05 quantile regression lines of the four minor species. Whereas, in Figure F.7 (MoE_{dyn}), western red cedar remained wholly above the all species 0.05 quantile regression line, in Figure F.8, western red cedar crosses the all species 0.05 quantile regression line and is the lowest of the four species for over half of the graph. However, the noble fir 0.05 quantile regression line generally lies below the all species datum in both graphs. This illustrates the changing nature of the relationships between the variables in the model and is a reason for using a multivariate model as opposed to using MoE_{dyn} on its own.

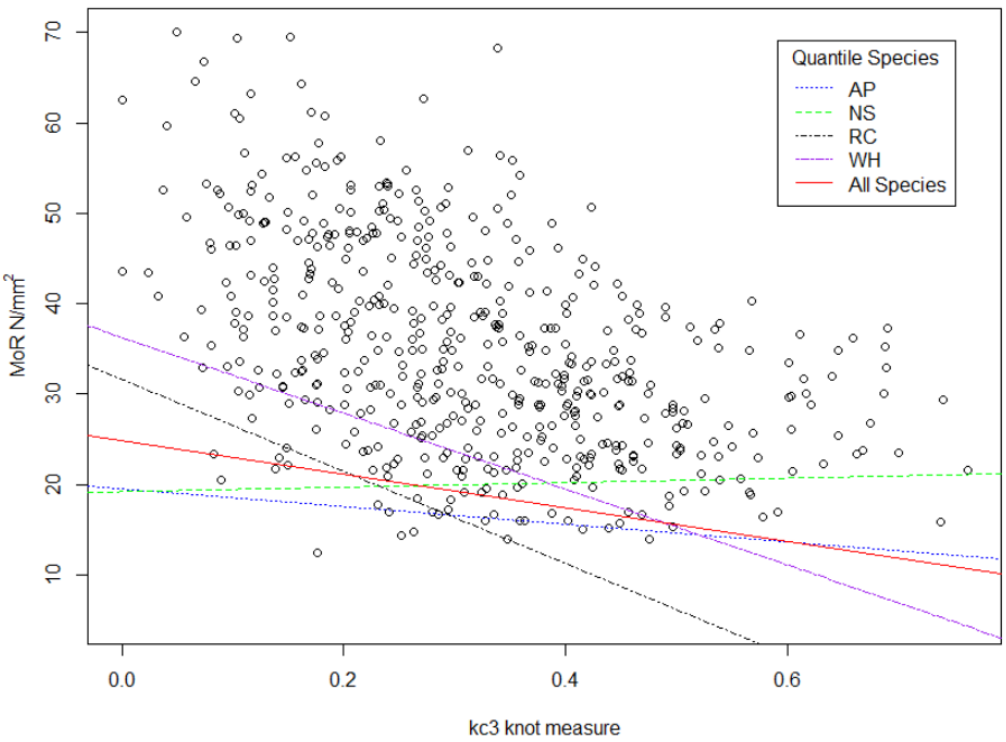

Figure F.8. Quantile plots of kc3 and MoR for four specific species and all species together

Additionally, from the 0.05 quantile plots for density, the species western hemlock and Norway spruce 0.05 quantile regression lines generally lie beneath the all species 0.05 quantile regression line. So, it is seen that each species' relationship between various predictor variables and MoR changes in relation to the all species relationships. Therefore, the most stable models are likely to be those that are based on several predictor variables.

F.3.2 Varying relationships between MoR and different variables

It is difficult to visualise the process and the outcomes of calculating the 0.05 quantile of MoR for a group of grading measures and then calculating the two sided 50% lower confidence limit for the same (for instance MoR vs. MoE_{dyn}, density and kc3). Therefore, to aid visualisation, a graph is presented which shows the relationship between the single grading parameter MoE_{dyn} with MoR, with median (dotted blue line), 0.05 quantile (dashed green line) and its attendant upper (UCL) (purple) and lower (LCL) (black) two sided 50% confidence limits: Figure F.9. The graph is based on a bootstrapping non-parametric analysis and shows how the 0.05 quantile diverges from the median. An alternative graph based upon an assumed distribution and an OLS regression model would show the mean and differ significantly from this. With OLS regression, the 0.05 quantile would be parallel to the mean and its attendant 50% confidence interval would be based on a noncentral t-distribution which in turn would be dependent on assumptions regarding the distribution of data (it should be borne in mind that the data is heteroscedastic). For the MoE_{dyn} vs MoR relationship, the 0.05 quantile and median lines diverge significantly. The solid red line connects the lowest LCL with the highest LCL data points and as such provides a linear baseline on or above which the LCL will always be found.

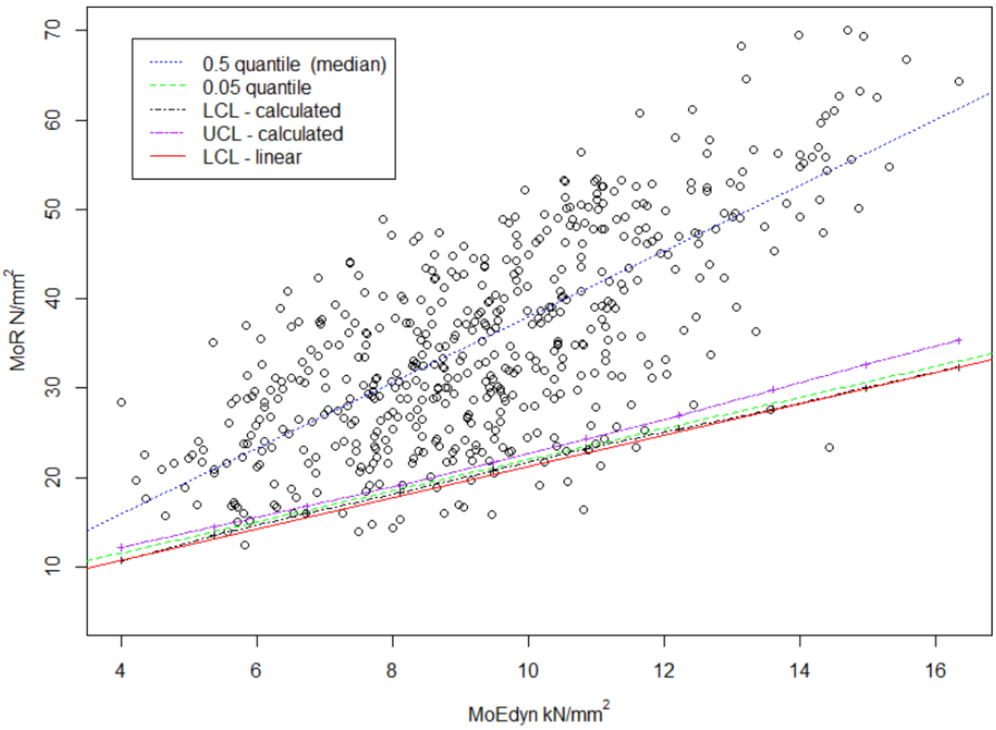

Figure F.9. Scatter plot of MoR vs. MoE_{dyn} with median, 0.05 quantile its confidence limits

With regard to other grading parameters, it is also useful to consider Table F.7 which presents key values of the 50% confidence interval around the 0.05 MoR quantile. The knot cluster measure kc3 includes all four sides of a joist and kc9 includes just the two vertical faces and as such only has around two thirds of the knot information of kc3. The relationship between kc3 and MoR would therefore be expected to be stronger than kc9 and MoR. This manifests itself in the results of the analysis as kc3 having a greater range of LCL values than kc9. The greater range is an indication of a steeper slope of the LCL, which (when used to estimate MoR from knot measures) differentiates more strongly the MoR estimates according to knot measures (i.e. a fixed change in kc3 knot measure produces a greater change in MoR estimate than for kc9). The small sample size must be borne in mind when reading these comments.

The weakness of SoG as a grading parameter is shown by the small range of 4.41 N/mm^2 and the strength of MoE_{dyn} is shown by its range of 21.60 N/mm^2. On this basis, density is seen to be a slightly better parameter than the two knot measures.

Table F.7. Maximum and minimum values of the 50% confidence limits around the 0.05 MoR quantile (N/mm^2) for five grading measures

	Min confidence interval	Min 50% LCL	Max 50% LCL	Range of LCL
MoE_{dyn}	0.78	10.71	32.31	21.60
Density	1.15	9.22	23.54	14.32
SoG	1.44	12.34	16.75	4.41
kc3	0.81	14.07	26.16	12.09
kc9	0.52	10.56	21.22	10.66

As is explained for MoE_{LCL}, the linear formulae for the estimation of the MoR_{LCL} have been determined for a range of single predictors and are compared by converting the predictor variable values to a range of between 0 and 100 (i.e. a percentage scale). Four equations of the linear estimates of MoR_{LCL} for the predictor variables MoE_{dyn}, kc3, density and SoG are presented below to illustrate the outcomes of the model building:

$$MoR_{LCL} = 3.725 + 1.749\ MoE_{dyn} \tag{F.4}$$

$$MoR_{LCL} = 23.54 - 18.776\ kc3 \tag{F.5}$$

$$MoR_{LCL} = 17.085 - 0.2370\ SoG \tag{F.6}$$

$$MoR_{LCL} = 0.996 + 0.0435\ density \tag{F.7}$$

In Figure F.10, below, the data points of three single predictor variables (MoE_{dyn}, SoG and kc3) and their linear estimates of MoR_{LCL} are shown. This graph differs from the one for mean MoE_{LCL}, as the 0.05 quantile MoR_{LCL} linear estimates are located close to the outer lower bound of the distributions and thus account to some degree for the wider distributions of the estimates based on the weaker predictors. So, as correlation reduces, each linear estimate moves lower in the graph, and SoG is seen to be a poor predictor. Thanks to this effect, the discussion regarding the need to penalise the poorer predictive models is not as pressing as it is for MoE_{LCL}. However, it still needs addressing along with the rating of models for use in practice.

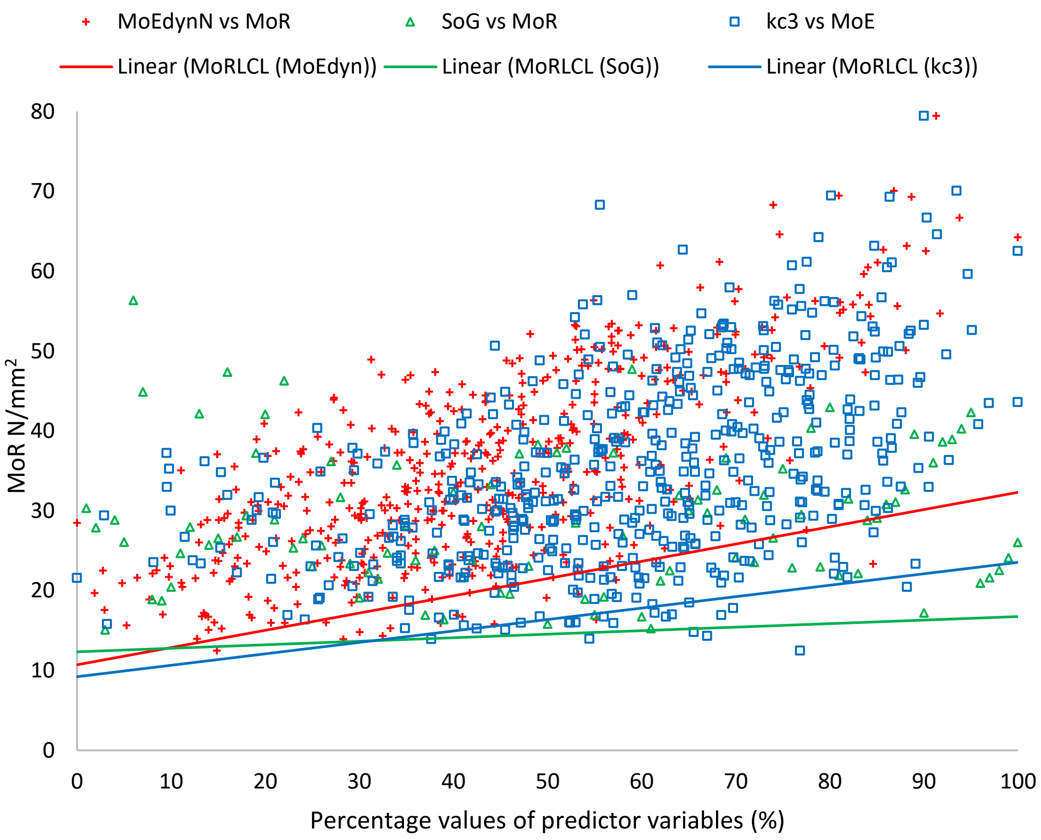

Figure F.10. Estimated MoR_{LCL} with normalised predictor variables

F.3.3 Adjustment of prediction equations

Reference should be made to the discussions on the adjustment and rating of predictive models for MoE_{LCL}. Once again, it is necessary to adjust models that may over-predict and to rate models to differentiate between those that can practically be used to predict MoR_{LCL} and those than cannot. Five models for MoR_{LCL} are shown in Figure F.11 below, showing that, for kc3 and kc9, there are no significant issues of over-prediction compared to MoE_{dyn}. Only density significantly over predicts below the ‘crossover’ at around 35% and SoG very slightly overpredicts. Also, the SoG line has the flattest of all gradients.

Based on the entire minor species data set, the 0.05 quantile of MoR and its 50% two sided lower confidence limit is calculated for the sample using bootstrapping to be 17.07 N/mm^2. Reference to Table 4.4 shows that the calculated characteristic values of MoR for each of the visual grades of BS4978 are similar. These figures are greater than any estimate for SoG and greater than most of the density estimates below the ‘crossover’.

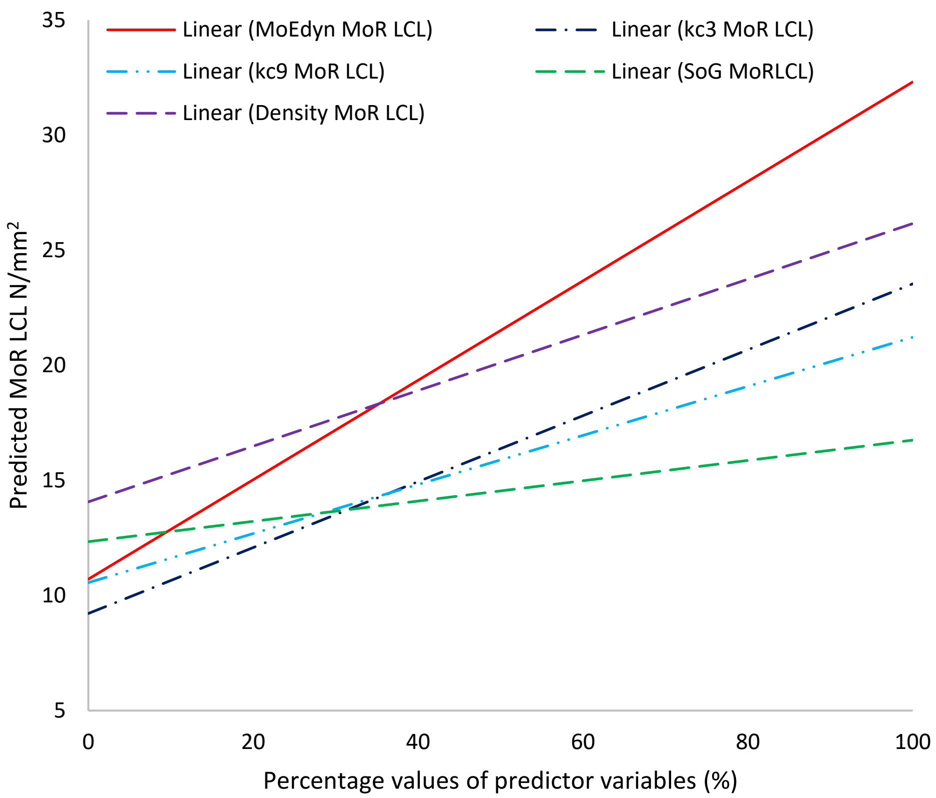

Figure F.11. Estimates of single predictors for MoR_{LCL}

Nevertheless, the weaker predictive models require adjustment. It is proposed that the same method that is used for MoE_{LCL} should be used for MoR_{LCL} and that the adjusted equations for each variable are based on the lowest value of the predicted MoR_{LCL} using the ‘best’ model and the equations are

$$Adjusted\ \ MoR_{LCL} = 0.258 + 1.961\ MoE_{dyn} \tag{F.8}$$

$$Adjusted\ MoR_{LCL} = -11.451 + 0.065\ density \tag{F.9}$$

$$Adjusted\ \ MoR_{LCL} =\ 23.54 - 20.258\ kc3 \tag{F.10}$$

$$Adjusted\ \ MoR_{LCL} =\ 21.22 - 15.195\ kc9 \tag{F.11}$$

$$Adjusted\ MoR_{LCL} =\ 17.408 - 0.465\ SoG \tag{F.12}$$

All of the single multivariate models are rated according to the ranges of their predicted values and only the MoE_{dyn} model is rated at three stars and is thus recommended for practical use. All others rate only one or two stars and are not recommended. Please refer to Table 8.4.

F.3.4 Natural log of the knot measure

From Chapter 5, it is seen that the transformation of the natural log of the knot ratio kc3 leads to an increase in correlation with MoR. As such, this transformation (lnkc3) was investigated further to see if it is worthwhile making this change. Figure F.12 shows a scatter plot of the natural log of the knot ratio plotted against MoR. The bunching of the data points to the right of the graph is seen in relation to the few outlying data points on the left.

In Figure F.12, the full lines are the mean of partial OLS regression and the median of quantile regression. The dotted lines are the 0.05 percentile. Blue and red lines represent partial OLS regression, with blue for the full data set (including the two data points with zero kc3 values), and the red lines represent the reduced data set (excluding two data points with zero kc3 values).

Green and black lines represent quantile regression, with green for the full data set (including the two data points with zero kc3 values), and the black lines represent the reduced data set (excluding the two data points with zero kc3 values). This is summarised below.

			Full set	Reduced set
Quantile regression	Median	Full line	Green	Black
	0.05 quantile	Dotted		
OLS regression	Mean	Full line	Blue	Red
	0.05 quantile	Dotted		

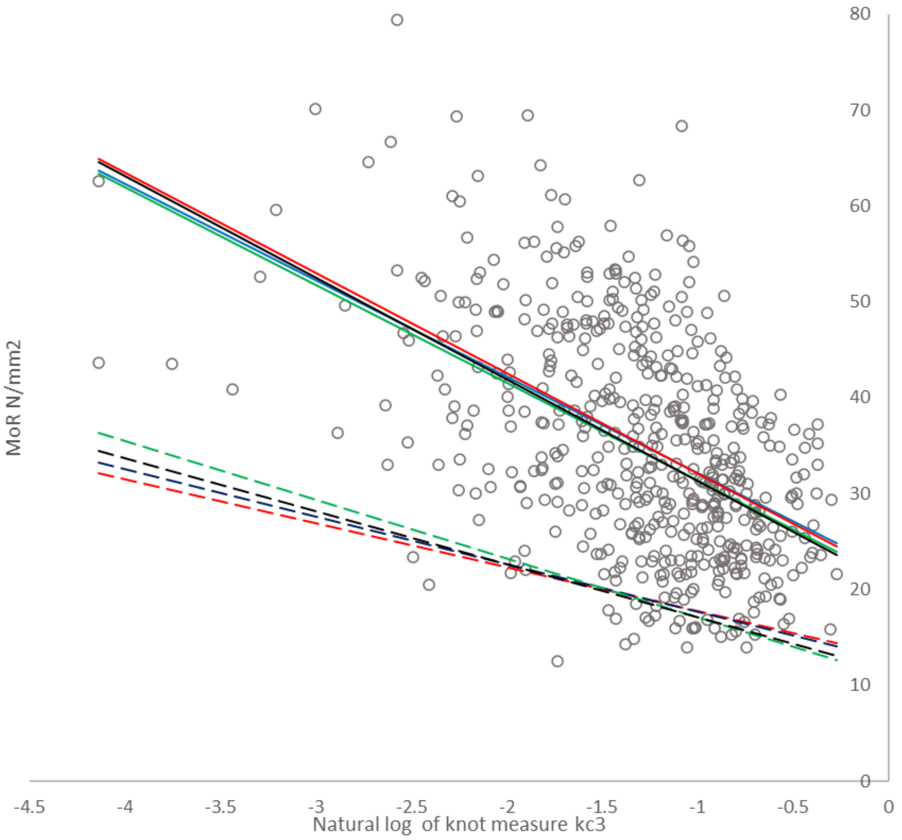

Figure F.12. Scatter plot of MoR vs natural log of knot measure kc3 (n=527)

For the partial OLS regression, the 0.05 quantile line is based on the splitting of the ln knots data into nine bins and calculating the 0.05 quantile for each of the bins in turn, plotting these onto the graph and then determining the OLS linear estimate through these points (this approach is different to but closely mirrors the method of quantile regression).

The two outliers on the left of the graph relate to two timber joists which had no knots within their central sections and recorded a kc3 knot measurement of zero. There is no natural log of zero and so in place of zero, a knot measurement of 0.016 was inputted for kc3 which gives a natural log of -4.11 (the value for lnkc3). The value 0.016 relates to a single 4.9mm knot found in a 50mm x 100mm section. As only knots of 5mm and above are recorded in this data set, this is a feasible replacement of zero. The alternative to changing the zero knot ratios in this way was to redact the two data points. This is not reasonable as the population of in situ existing timber joists is expected to include many timber joists without knots along at least a part of their lengths and these joists would be excluded from the model.

This outcome of this substitution of values is of interest for two reasons. Firstly, as there is a good chance of encountering in situ joists with no knots over the part of their length under assessment, the possible problem of using natural logs in a quantile regression model is highlighted. Secondly, the two outliers (with MoR values of 43.6 and 62.5 N/mm^2) are seen to have a noticeable effect on the mean, the median and 0.05 quantile trend lines.

A similar exercise was carried out (first, including the two outliers and then excluding them in model building); this time based on the quantile regression model of MoR with kc3 (i.e. not log transformed). For these two models, the median and 0.05 quantile lines remain constant regardless of the inclusion or otherwise of the outlying data points. Bearing in mind the noticeable effect that the two outliers have on the model using the natural log of the knot measure, it is considered best not to use the natural log transformation of the knot measure in any final predictive model.

The results presented above and the conclusion are surprising as, in much literature on quantile regression, it is presented as a model that is robust to outliers. In this instance, the outliers are due to the commonplace occurrence of a joist with no knots over part of its length.

Appendix G Published documents

All available from the University of Liverpool Repository and from the Staff Profile page of Mike Bather at the University of Liverpool

All available at: https://www.liverpool.ac.uk/engineering/staff/michael-bather/publications/ (All accessed: 17 January 2022).

Bather, M. (2022) Guide to statistics in the Eurocodes for timber engineers

Bather, M. (2022) Technical note on the determination of strength reduction factors using elastic analysis

Bather, M. (2022) Technical note on the determination of strength reduction factors using ASTM D245

Bather, M. (2022) Technical note on the use of visual grading codes for the appraisal of individual in situ structural timber elements

Bather, M., & Ridley-Ellis, D. J. (2019) The use of a visual grading code of practice in the UK in the assessment of the mechanical properties of in situ structural timber elements. In Proceedings of the International Conference on Structural Health Assessment of Timber Structures (pp. 89-98). Guimaraes, Portugal

Bather, M., Ridley-Ellis, D. J., & Gil-Moreno, D. (2016) Combining of results from visual inspection, nondestructive testing and semi-destructive testing to predict the mechanical properties of western hemlock. In WCTE 2016 e-book : containing all full papers submitted to the World Conference on Timber Engineering (WCTE 2016), August 22-25, 2016, Vienna, Austria (pp. 5131-5140). Vienna: TU Verlag Wien. Retrieved from http://hdl.handle.net/20.500.12708/172