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DEVELOPING A FUZZY NEW-GENERATION WHOLE-LIFE COST MODEL FOR MEDIUM-SIZED OFFICE BUILDINGS.

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ABSTRACT

Purpose of this paper
The purpose of this paper is to explore the investment appraisal aspects of the new-generation whole-life cost (NWLC) model and develops a fuzzy new-generation whole-life cost model for 25 simulated configurations of a steel-type medium sized office building

Design/methodology/approach
This work builds on the new-generation whole-life cost model attributed to Ellingham and Fawcett (2006) and replaces the binomially derived probability values by a fuzzy relation matrix using the cosine amplitude formulae.

Simulated cost data of a medium-sized office building were computed using the existing whole-life cost techniques. The cost data were then analysed using the Spearman's rank order correlation coefficient to assess the correlation in the preferences of clients based on each model

Findings and value
This work reveals a perfect correlation between the standard whole-life cost model and the fuzzy lower new-generation whole-life cost model. Equally, there is a strong correlation between the new-generation whole-life cost model and the fuzzy upper new-generation whole-life cost model.

Research limitations/implications
This research examined only 25 building configuration permutations and the statistical tests were conducted at a 90% confidence interval level. Equally, the results are consistent for typical steel curtain baseline office buildings in the Philadelphia region of the United States.

Practical implications
Employing fuzzy set theory in modelling uncertainty in whole-life costing provides a sufficient and robust template for evaluating the cost implications over the estimated life of a building.

Originality/value of paper
This paper provides a robust technique that can assist decision-makers and facility managers in selecting the effective choice amongst a number of competing building configuration alternatives. This paper develops a new approach using fuzzy set theory for modelling uncertainty in the new-generation whole-life cost mechanism.

Conclusions:
It is instructive that a single-point whole-life cost estimate might be misleading for construction clients requiring conclusive guidance on the most economical option over the life of their built. Hence the range of whole-life cost values provided by fuzzy set theory is beneficial for construction clients in making more rational decision choices towards selecting an optimal configuration over the estimated life of the building

Keywords: fuzzy-set theory, new-generation, office-buildings, uncertainty, whole-life costing

1 INTRODUCTION

Investment in modern buildings requires comprehensive evaluation in order to ascertain economic viability. Mathematical modelling of whole-life costing provides a relevant framework to assess the investment potentials of such buildings. The standard whole-life costing (WLC) has been the general approach for evaluating the cost of a building over its expected life. Though, based on the simplistic net-present value metric, the standard whole-life costing methodology can arguably be considered the most widely-used approach for assessing the cost implication of a built facility over its expected life. Recent attention to real-options theory has provided a tangible supplement to the standard whole-life costing (WLC) methodology and has resulted in the development of the new-generation whole-life costing (NWLC) technique. Despite the advanced mathematical framework of the NWLC, it does not seem to fully handle the issues concerning the profile and treatment of uncertainties.

One approach to uncertainty modelling that allows for some degree of flexibility is the fuzzy sets framework. Fuzzy set theory basically imply the inclusion of degree of belonging in evaluating variables ((Zadeh 2008). They help to capture irreducible uncertainty as well as model vagueness in human reasoning abilities. Fuzzy relations are special cases of fuzzy sets. Fuzzy relations can be defined as a vague relationship between some fixed numbers of variables (Zimmermann 2001). Relations are useful in interpreting the attributes of fuzzy systems. Fuzzy relations are essentially one means of modelling the intensity between elements of a fuzzy set. Given the attributes and functions of fuzzy relations, it could be effectively used in representing uncertainties in the whole-life cost evaluation of buildings.

A primary essence of whole-life costing in buildings is the comparison of alternatives which could assist in selecting building configurations that balance a good design with functional performance (Caplehorn, 2012). In the existing literature on whole-life costing, two different structures of whole-life cost models have been identified. While the standard whole-life cost (WLC) model primarily serves as an investment appraisal technique, the new-generation whole-life cost (NWLC) model has been further enhanced into a decision-making framework, over the life of a building. This paper aims to explore the investment appraisal aspects of the NWLC and develops a fuzzy new-generation whole-life cost model for 25 simulated configurations of a steel-type medium sized office building. The fuzzy relation is developed based on the transformation of binomial probability coefficients of the new-generation whole-life cost model. The fuzzy transformation leads on to the evaluation of the respective fuzzy lower, fuzzy mean and fuzzy upper new-generation whole-life cost values for each of the 25 building configuration permutations. The cost values are then transformed into ranked pairs for each whole-life cost model and the ranking pairs are then correlated based on the Spearman's rank order correlation.

An overview of whole-life costing is discussed in the next section. After which, a review on the approaches to modelling uncertainty is examined. The research method is discussed in the subsequent sections, along with the results from the study. A discussion on the benefits of this approach is then treated and directions for future research are suggested.

2 BACKGROUND: WHOLE-LIFE COSTING

The subject of whole-life costing relates to the systematic evaluation of the cost of a facility over its expected life. According to the CIFPA (2011), whole-life costing is simply the systematic consideration of relevant costs and revenues associated with acquisition and ownership of a project over its estimated life. Despite a fairly abundant literature on whole-life costing across various disciplines, it remains to be proven whether existing whole-life cost models actually reflect the costing realities in built facilities (Clift and Bourke 1999, Ellingham and Fawcett 2006, Fawcett *et al.* 2012, Ferry, Brandon and Ferry 1999, Kirkpatrick 2000, Kishk 2005, Malik 2012). A major concern on the performance of existing whole-life cost models mostly relates to the inexactness in the running costs projections. Ferry *et al.,* (1999) reckons that the estimation of the running costs in built facilities is often a product of guess work and will be dependent on a mix of personal preferences and policy standards. A logical approach to overcoming this misalignment between theory and practice of whole-life costing may suggest the accumulation of actual cost data over a building's life and comparing them to the estimated costs from whole-life cost models. This approach will however require enormous time and efforts, and may still be froth with biases. In the UK, for example, companies are only legally obliged to keep such data for a period of 3 years after which they can be discarded. Hence availability of data may prove to be a daunting challenge (Bordass 2000, Kishk and Al-Hajj 2000, Tietz 1987). Even in instances where such data have been meticulously kept and can be made available, such exercise could still be seen as grossly intrusive and give rise to privacy concerns (Callaghan, Clarke and Chin 2009). More so, in residential buildings, there is not much legislation regarding the retention of cost data. Hence, there has been a clear gap in establishing the usefulness and limitations of existing whole-life cost models.

In the current literature on built facilities, two different mathematical models of whole-life costing have been developed. The first one, more commonly known in the construction industry is the standard whole-life cost model. The more recent one, termed the new-generation whole-life cost model is attributed to Ellingham and Fawcett (2006). Table 1 reports on the essential attributes of these two models.

Table 1. Comparative Difference in Existing Whole-life Costing Techniques

	Property	*Standard Whole-life Cost Technique*	*New-Generation Whole-life Cost Technique*
1	**Mathematical Form**	Closed-form Expression	Binomial Expansion
2.	**Uncertainty Assumption of Cash flows**	None	Bivariate
3.	**Risk Analysis Methodology**	Not Applicable	Probabilistic
4.	**Effect of Inflation and Discounting**	Inflation and discounting and jointly computed	Inflation and discounting are separately computed
5	**Evaluation mechanism**	Discrete summation only	Discrete Summation and Decision-tree analysis
6.	**Time-Value of Cash flows**	Exponentially Declining	Linearly declining or ascending

Cost estimation in built facilities generally take account of the objectives and requirements of a cost system, as well as its constraints and assumptions (Tokede, Sloan and Brown 2013). Conceptually, the paths to cost-modelling are often a choice between simulation and mathematical modelling (Farr 2011). Mathematical cost models could be useful and effective wherever data inputs are certain, have little or no variability and are available. Such instances may by implication ignore the existence of uncertainties (as observed with the standard whole-life cost technique, see Table 1). Given the scope of whole-life costing, this approach of ignoring uncertainties in the model framework, may conceal crucial aspects of the model. Nevertheless, mathematically cost modelling has been the pervasive approach used in the whole-life costing of built facilities and till date it is yet to be seen that building clients take notice of it in investment appraisal situations (Caplehorn 2012).

An alternative to the use of mathematical models in whole-life costing is the simulations technique. Simulations are a cheaper way to conduct a simplified analysis of a system (Farr 2011). Simulations however fail to establish fundamental relationships and may provide outputs based on unverified or static assumptions. Boussabaine and Kirkham (2008) also expressed that simulations are more of a satisfactory than an optimal alternative in cost modelling.

There is however a growing body of opinion that for whole-life cost models to be useful and true to its function, the existence of uncertainties has to be acknowledged and provided for in its model framework (Bankole *et al.* 2012, Gluch and Baumann 2004, Verbruggen, Marchohi and Janssens 2011). Core areas of uncertainties in cost estimation include: cashflow data, building-life, investor's commitment, component service life and future decisions. Uncertainties, have been defined as lack of information which could stem from cognitive sources and non-cognitive sources (Ayyub 2006). An understanding of the exact nature of uncertainties affecting respective variables in whole-life costing situations will go a long way in better representing variables over the expected life of a built facility. A review on the specific features of the existing whole-life cost models will be examined:

2.1 Standard Whole-life Cost Model (WLC)

The standard whole-life cost model dates back at least to Flanagan and Norman (1983), through a funded research by the Royal Institute of Chartered Surveyors [RICS] Education Trust. Since then, there has been a progression of studies on the subject of whole-life costing. Cole and Sterner (2000) documented and distinguished between the nomenclatures of whole-life costing which includes full cost accounting, total cost accounting and life-cycle cost accounting. Other related approaches to whole-life costing not explicitly reported by Cole and Sterner are through-life costing, total costing and whole-life cycle costing. It was however, Kishk (2005) that conjectured that all this variants are based on the same closed-form mathematical algorithms. Park and Sharpe (1990) explained that closed-form mathematical algorithms normally converge to a particular value.

Generally, the standard whole-life costing employs the present-value metric hinged on the discounting technique to evaluate the cost of built facilities. Mathematically, the standard whole-life cost formulae can be represented as:

$$WLC = \sum_{t=0}^{T}\left(\frac{C_{it}}{(1+d)^{t}}\right) \tag{1}$$

Where C_{it} = Equivalent cash flow, $d = \text{discount rate}$ and $t, T = \text{time (in years)}$

Conceptually, the standard whole-life cost mechanism sums up the present-value figure of the respective time of occurrence (usually years) of an estimated cost. Hence, the standard whole-life cost technique is more generally termed the “Net Present-Value” in whole-life cost evaluation scenarios. The present-value figure for each year is obtained based on the discounting technique, which involves the use of a discount-rate to exponentially scale-down the numerical value of a projected cost, relative to its expected time of occurrence. The farther into the future a project cost, the lesser its value relative to the present time.

2.2 New-Generation Whole-life Cost Model (NWLC)

The New-Generation Whole-life Costing technique was introduced by Ellingham and Fawcett (2006). The philosophical difference between the new-generation whole-life costing and the standard whole-life costing lies in the inclusion of uncertainty in the model framework. The assumption regarding the uncertainty in cash flow values is represented in binomial form – implying a proportionate increase or decrease in cashflow values over the expected life of a built facility. The chances for the occurrence of each cashflow were obtained by a normalized probability figure based on the binomial theorem. An exemplar on the probability-coefficient assumptions and binomial cashflow values is shown in the Figure 1 and Figure 2 respectively, representing the probability coefficient and the respective binomial cashflow projections for the first four years of a built facility, starting from year 0.

$$\begin{array}{c}
\begin{array}{ccccc} \mathbf{0} & \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{array} \\
\begin{bmatrix}
 & & & & {}^{4}C_{0} \\
 & & & {}^{3}C_{0} & \\
 & & {}^{2}C_{0} & & {}^{4}C_{1} \\
 & {}^{1}C_{0} & & {}^{3}C_{1} & \\
{}^{0}C_{0} & & {}^{2}C_{1} & & {}^{4}C_{2} \\
 & {}^{1}C_{1} & & {}^{3}C_{2} & \\
 & & {}^{2}C_{2} & & {}^{4}C_{3} \\
 & & & {}^{3}C_{3} & \\
 & & & & {}^{4}C_{4}
\end{bmatrix}
\end{array}
\qquad
\begin{array}{c}
\begin{array}{ccccc} \mathbf{0} & \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{array} \\
\begin{bmatrix}
 & & & & 18{,}883.86 \\
 & & & 18{,}157.56 & \\
 & & 17{,}459.19 & & 17{,}459.19 \\
 & 16{,}787.68 & & 16{,}787.68 & \\
16{,}142.00 & & 16{,}142.00 & & 16{,}142.00 \\
 & 15{,}521.15 & & 15{,}521.15 & \\
 & & 14{,}924.19 & & 14{,}924.19 \\
 & & & 14{,}350.18 & \\
 & & & & 13{,}798.25
\end{bmatrix}
\end{array}$$

Figure 1. Probability Coefficients in NWLC

Figure 2. Binomial Cashflow Values (*4% increase annually*)

The major issue that arises in comparing the standard whole-life cost model with the new-generation whole-life cost model is that the former ignores the uncertainties in cashflow values, while the later imposes an unverified pattern for uncertainty - which may as well be wrong.

The central contribution of the new-generation whole-life cost model appears to be its admittance of an existential uncertainty in cash flow values, over the life of a built facility. This level of awareness on the existence of uncertainties in the cashflow projection of whole-life cost models, regardless of the simplicity, remains an invaluable contribution from the new-generation whole-life cost model. Besides, it provides a systematic and tractable approach to whole-life costing within the limitations of a mathematical modelling framework.

3 MODELLING UNCERTAINTY

In modelling uncertainty, probability theory is often the traditional and widely-accepted mechanism across various disciplines (Zadeh 1995). According to Raftery(2003), there are three common approaches to evaluating probability-values. These are: an objective calculation based on observed relative frequencies of past incidences; prior basis derived from visible symmetry and personalistic or subjective approach. All these approaches tend to provide a single-value figure representing the likelihood of occurrence of an uncertain event. There have however been a number of concerns on the sufficiency of such single-value estimate in capturing the entire facets of uncertainty (Dubois *et al.* 2004, Kosko 1990, Zadeh 1995) since it principally provides information on the likelihood of an uncertain event. According to Ayyub and McCuen (2011), uncertainties may be classified as vagueness, likelihood and/or ambiguity. While probability theory may be appropriate for dealing with uncertainties regarding the likelihood of events (Kishk and Al-Hajj 2000, Kosko 1990), it could prove insufficient to deal with the vagueness and ambiguity aspects inherent in event occurrence (Zadeh 1995, 2008, Zimmermann 2001). More generally, Zadeh (1995, pp274) states that “probability theory tends to be much less effective in situations where dependencies between variables are not well-defined, the knowledge of probabilities is imprecise and/or incomplete, the systems are not mechanistic, and human reasoning perceptions and emotions do play an important role”. These situations highlighted by Zadeh are arguably typical to whole-life costing scenarios and hence the applicability of fuzzy sets needs to be keenly considered.

A complementary approach to handling the aspects of uncertainty regarding vagueness and ambiguity is fuzzy set theory (Zadeh 1995). Belohlavek *et al.,* (2009) defined fuzzy set theory as a calculus that can be used in formalizing our intuitions about composition of graded categories. Baloi and Price (2003) clearly expressed that fuzzy set theory is not intended to replace probability theory but rather to provide solutions to problems that lack mathematical rigour. Other benefits with the fuzzy set approach are: they provide a tool to address variability associated with human abilities and performance (Mccauley-Bell and Badiru 1996); they provide a more flexible structure for combining qualitative and quantitative information (Sii, Ruxton and Wang 2001); they provide a way to deal with ill-defined and complex problems (Dikmen, Birgonul and Han 2007); they add value to the quality of decision-making (Byrne 1997) and allow for a reasonable trade-off between information usage and practical problems solving (Zadeh 2008).

There are two resounding similarities between probability theory (PT) and fuzzy set theory (FST) in handling uncertainties. Both describe uncertainty with numbers in unit interval (0, 1) and both combine set propositions; associatively, commutatively and distributively (Kosko 1990). The authors of this paper have also observed that another distinction between both fuzzy set theory and probability is that while probability provides information based on the pattern in information available and accessible, fuzzy set theory attempts to model uncertainty based on the structure of the information available and accessible. Kosko (1990) however provides a more abstract distinction between PT and FST, which is in the manner of treatment of a set (A) and its set-theoretic opposite (A^c).

Given, the practical possibilities engendered by fuzzy set theory in uncertainty modelling, this study explores the fuzzy approach in modelling the new-generation whole-life cost of buildings. This approach will be important as more facets of uncertainty could be captured and more so, being a new approach to modelling whole-life costs could provide a more robust and realistic alternative to the closed-form mathematical expressions commonly used in practice.

4 FUZZY NEW-GENERATION WHOLE-LIFE COST MODEL

The background literature on fuzzy set theory can be found in Ross (2009). One key aspect in the fuzzy set approach to uncertainty modelling is the development of a membership function. Membership functions represents the degree of similarity of different objectives of a defined parameter (Shaopei 1998). Membership functions also help to characterize the relationship between parameters and could be used to translate subjective terms into mathematical measures (Kim *et al.* 2006) .As previously noted, in situations where no variability exists, closed-form algorithms, simple observation and Cartesian products may be effective approaches to developing the membership function (Ross 2009). However, where variability exists, membership values on the interval [0, 1] may lead to the development of fuzzy relation. In such situations, an observable pattern may be assumed and hence a fuzzy relation may be developed based on linguistic knowledge from experts, use of look-up tables and other specialized pattern classification mechanisms. In situations where the structure of the uncertainty needs to be considered, fuzzy relations may be more aptly determined through similarity methods that attempt to model some sort of structure in data. There are many methods available but the most prevalent are the cosine-amplitude and the max-min methods (Ross 2009). Some authors on fuzzy set theory has termed the max-min method, a conservative solution because it employs the goodness of one value to compensate the badness of another (Loetamonphong and Fang 2001). This work will utilise the cosine-amplitude similarity metric in developing a fuzzy new-generation whole-life cost model

The similarity metric makes uses of a collection of data samples, k, and assumes they form a data array, K

$$K = \{k_1, k_2, \ldots, k_n\}$$

Each of the elements, k_i, is itself a vector of length m, i.e. $k_i = \{k_{i1}, k_{i2}, \ldots, k_{im}\}$, Each element of a relation, r_{ij}, results from a pairwise comparison of two data samples, k_i and k_j, the relation matrix will be of size, n x n. the cosine method calculates, r_{ij}, in the following manner and guarantees that $0 \le r_{ij} \le 1$:

$$r_{ij} = \left(\frac{\sum_{l=1}^{m} k_{il} k_{jl}}{\sqrt{\left(\sum_{l=1}^{m} {k_{il}}^2\right)\left(\sum_{l=1}^{m} {k_{jl}}^2\right)}} \right) \tag{2}$$

In the classical new-generation whole-life cost model developed by Ellingham and Fawcett (2006), probability values based on the binomial assumption is utilised in computing the respective present-value cost figures over the expected life of a built facility. In the fuzzy new-generation whole-life cost model developed, the probability values derived by the binomial model framework can all together be converted into a fuzzy relation. In order to however, retain the relation matrix, to be of n x n dimensions, zeros will be inserted in the empty spaces, as seen in figure 3 below

$$\begin{array}{c} \begin{array}{ccccc} \mathbf{0} & \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{array} \\ \left[\begin{array}{ccccc} & & & & 0.0625 \\ & & & 0.125 & \\ & & 0.25 & & 0.25 \\ & 0.50 & & 0.375 & \\ 1.00 & & 0.50 & & 0.375 \\ & 0.50 & & 0.375 & \\ & & 0.25 & & 0.25 \\ & & & 0.125 & \\ & & & & 0.0625 \end{array}\right] \end{array} \quad \begin{array}{c} \begin{array}{ccccc} \mathbf{0} & \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{array} \\ \left[\begin{array}{ccccc} & & & & 18{,}883.86 \\ & & & 18{,}157.56 & \\ & & 17{,}459.19 & & 17{,}459.19 \\ & 16{,}787.68 & & 16{,}787.68 & \\ 16{,}142.00 & & 16{,}142.00 & & 16{,}142.00 \\ & 15{,}521.15 & & 15{,}521.15 & \\ & & 14{,}924.19 & & 14{,}924.19 \\ & & & 14{,}350.18 & \\ & & & & 13{,}798.25 \end{array}\right] \end{array}$$

Figure 3. Probability Coefficients arranged in matrix and binomial cash flow values (inset right)

Using the cosine amplitude formulae in eqn (2), the probability values arranged in matrix form in figure 3 is converted into a fuzzy relation. The fuzzy relation is then used with each of the binomial cash flow values to derive the fuzzy lower, fuzzy mean and fuzzy upper cash flow values. The computations for the fuzzy relations are implemented with scripts written on a computer software package - Python®

$$\begin{array}{c}\begin{matrix} \mathbf{0} & \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{matrix} \\ \begin{bmatrix} 1.00 & 0 & 0.82 & 0 & . \\ 0 & 1.00 & 0 & 0.95 & . \\ 0.82 & 0 & 1.00 & 0 & . \\ 0 & 0.95 & 0 & 1.00 & . \\ 0.72 & 0 & 0.98 & 0 & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ 0.46 & 0 & 0.72 & 0 & . \end{bmatrix}\end{array} \quad \begin{array}{c}\begin{matrix} \mathbf{0} & \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{matrix} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 18{,}883.86 \\ 0 & 0 & 0 & 18{,}157.56 & 0 \\ 0 & 0 & 17{,}459.19 & 0 & 17{,}459.19 \\ 0 & 16{,}787.68 & 0 & 16{,}787.68 & 0 \\ 16{,}142.00 & 0 & 16{,}142.00 & 0 & 16{,}142.00 \\ 0 & 15{,}521.15 & 0 & 15{,}521.15 & 0 \\ 0 & 0 & 14{,}924.19 & 0 & 14{,}924.19 \\ 0 & 0 & 0 & 14{,}350.18 & 0 \\ 0 & 0 & 0 & 0 & 13{,}798.25 \end{bmatrix}\end{array}$$

Figure 4: Fuzzy Matrix Relation of Binomially derived Probability values and binomial cash flow values (inset left)

5 RESEARCH METHOD

The cost data used in this research was based on a simulation of energy conservation measures (see Table 2 below) using the EnergyPlus software. EnergyPlus provided the annual consumption for the combinations of the simulated baselines. Since combination of the 14 baselines will produce as many as 87,178,291,200 (14!) possible combinations, it may be more efficient to utilise field experience and engineering judgment to estimate the impact of these combinations on cost-savings. The various combinations were therefore scaled based on the context specific end-user factors which considers the presence of Interior Lighting (I.L), Exterior Lighting (E.L), Hot Water (H.W), Heating (H), Cooling (C), Pumps and Condensers (P-C), Fans (F), Elevators (E) and Small Plug Loads (SPL). These were scaled annually accordingly as shown in Table 1, and followed on the work of Hendricken (2012).

Table 2 Energy Conservation Measures and respective scaling based on EnergyPlus Modelling and Engineering Judgment

Energy Conservation Measures	I.L	E.L	H.W	H	C	P-C	F	E	SPL
Steel curtain baseline	100%	100%	100%	120%	120%	120%	120%	100%	100%
T-5 lighting upgrade	54%	100%	100%	141%	81%	100%	77%	100%	100%
LED light tube upgrade	12%	15%	100%	145%	80%	100%	77%	100%	100%
High efficiency elevator upgrade	100%	100%	100%	100%	100%	100%	100%	50%	100%
Double pane window upgrade	100%	100%	100%	75%	75%	100%	100%	100%	100%
Temperature reset strategy	100%	100%	100%	89%	90%	100%	100%	100%	100%
High-efficiency central boiler	100%	100%	100%	70%	100%	100%	100%	100%	100%
Variable-air-volume system upgrade	100%	100%	100%	100%	60%	100%	100%	100%	100%
Dedicated outdoor-air	100%	100%	100%	82%	42%	100%	65%	100%	100%
Central chiller plant upgrade	100%	100%	100%	33%	33%	100%	100%	100%	100%
High efficiency central chiller	100%	100%	100%	33%	23%	100%	100%	100%	100%
Variable-air-volume system upgrade	100%	100%	100%	88%	90%	100%	50%	100%	100%
Heat pump	100%	100%	100%	100%	98%	100%	99%	100%	100%
Ground-source heat pump	100%	100%	100%	80%	80%	100%	100%	100%	100%
Dedicated outdoor air system upgrade	100%	100%	100%	10%	10%	100%	100%	100%	100%
White roof upgrade	100%	100%	100%	100%	100%	100%	100%	100%	100%
Insulated walls upgrade	100%	100%	100%	100%	100%	100%	100%	100%	100%

By scaling the factors attached with energy-conservation measures using field experience and engineering judgment, the total number of possible combinations was reduced to 25 building configuration permutations (BCPs). Data was then gathered on the initial cost and maintenance cost from the RSMeans (Reeds Construction Data, 2011). The data was then combined with the energy-consumption equivalents to compute the annual utilities (i.e. gas and electricity) cost of the various configurations of a typical steel-constructed medium-sized office buildings in the Philadelphia region of the United States. Table 3 reports the whole-life cost estimates of the 25 BCPs.

Table 3: Whole-life Cost Estimates of the 25 Building Configuration Permutations

BCP	WLC	NWLC	Fuzzy Lower NWLC	Fuzzy Mean NWLC	Fuzzy Upper NWLC
P1	2,029,589	2,583,238	2,032,350	2,402,492	2,537,244
P2	1,848,349	2,328,460	1,850,740	2,171,716	2,288,570
P3	1,791,760	2,178,955	1,793,689	2,052,547	2,146,786
P4	2,049,257	2,550,051	2,051,755	2,386,559	2,508,447
P5	1,877,534	2,372,287	1,880,001	2,210,768	2,331,185
P6	2,372,460	2,867,213	2,374,927	2,705,693	2,826,111
P7	2,133,169	2,534,214	2,135,165	2,403,282	2,500,891
P8	2,076,580	2,384,709	2,078,114	2,284,112	2,359,108
P9	2,476,314	2,940,722	2,478,631	2,789,109	2,902,141
P10	2,390,866	2,880,377	2,393,307	2,720,569	2,839,710
P11	2,391,844	2,859,567	2,394,177	2,706,872	2,820,711
P12	2,319,376	2,781,857	2,321,683	2,630,873	2,743,437
P13	2,206,321	2,566,183	2,208,112	2,448,695	2,536,282
P14	2,200,841	2,489,862	2,202,280	2,395,504	2,465,848
P15	2,138,137	2,527,079	2,140,072	2,400,098	2,494,762
P16	2,081,547	2,377,574	2,083,021	2,280,929	2,352,978
P17	2,495,692	2,951,022	2,497,963	2,802,373	2,913,196
P18	2,192,481	2,526,335	2,194,142	2,417,338	2,498,594
P19	2,157,461	2,406,754	2,158,702	2,325,365	2,386,040
P20	2,323,585	2,771,292	2,325,818	2,625,132	2,734,099
P21	2,305,464	2,746,152	2,307,661	2,602,283	2,709,542
P22	2,124,224	2,491,373	2,126,051	2,371,507	2,460,867
P23	2,067,634	2,341,868	2,069,000	2,252,338	2,319,083
P24	2,457,008	2,880,074	2,459,118	2,741,958	2,844,928
P25	2,145,470	2,446,283	2,146,966	2,348,073	2,421,287

The data obtained was then used to compute the standard whole-life cost (WLC), new-generation whole-life cost (NWLC), fuzzy lower new generation whole-life cost, fuzzy mean new-generation whole-life cost and fuzzy upper new-generation whole-life cost, over an assumed life of 25 years. Based on the work of Harrison (2010), a discount rate of 11.28% was used in the standard whole-life cost model. This value corresponded to an interest rate of 4% and discount rate of 7% in the new-generation whole-life cost models. The computed values were then analysed based on the Spearman rank-order correlation to examine the agreement in the ranking of the models.

The Spearman rank-order correlation (r_s) is used to compare the relationship between ordinal or rank-ordered variable. According to Corder and Foreman, (2009), the Spearman rank's correlation is applicable, if the sample size is more than or equal to four. According to Gaten (2000), the sample size should be between 7 and 30. The study restricted the number of BCPs to the first 25 which is considered adequate and realistic, to avoid any information overload for decision-makers

The choice of Spearman's rank-order correlation is based on the primary essence of whole-life costing as a technique for effectively selecting amongst a number of competing project alternatives. In the study herein, the study alternatives are the building configuration permutations. The ranking was done by sorting the BCPs from the least to the highest whole-life costs. This was implemented using the "Sort & Filter" option in Microsoft Excel 2010. The sorted cost figures were then ranked and compared for each of the whole-life cost models. The general formulae for the Spearman rank-order correlation is expressed in equation (3):

$$r_s = 1 - \left(\frac{6\sum D_i^2}{n(n^2-1)} \right) \tag{3}$$

Where n = number of rank pairs and D_i = Differences between ranked pairs

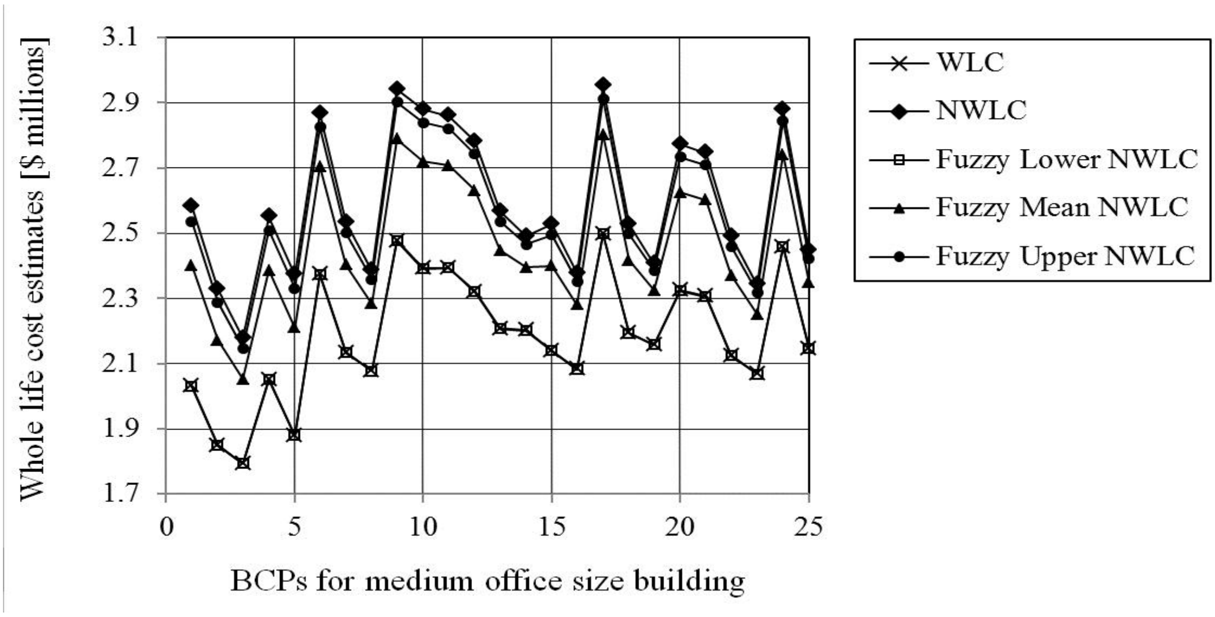

Figure 5: Building Configuration Permutations (BCPs) for medium-sized office buildings

Table 4: Coefficients of the Whole-life Cost Models based on the Spearman Rank Correlation Measure

	Correlation Coefficients				
Parameters	**Standard WLC**	**Classical NWLC**	**Fuzzy Lower NWLC**	**Fuzzy Mean NWLC**	**Fuzzy Upper NWLC**
Standard WLC	1.00	0.105*	1.00	0.325*	0.360
Classical NWLC		1.00	0.105*	0.343	0.793
Fuzzy Lower NWLC			1.00	0.325*	0.360
Fuzzy Mean NWLC				1.00	0.607
Fuzzy Upper NWLC					1.00

* Values are not statistically significance at the 0.1 level (2-tailed)

6 RESULTS AND DISCUSSION

The results obtained for the whole-life cost estimates for twenty-five building configuration permutations are shown in Figure 5. Based on a cursory observation, the data obtained shows a very high level of correlation between the fuzzy lower new-generation whole-life cost and the standard whole-life cost model. This basically implies that the difference between the new-generation whole-life cost and the standard whole-life cost is primarily a result of the uncertainty considered in the model framework. Where uncertainty or perhaps variability is lacking in the model inputs both models produce the same ranking values and thus clients preferences based on cost are perfectly the same.

The correlation coefficient between the remaining variants of whole-life costing was subjected to statistical analysis using the SPSS® (Statistical Package for Social Sciences) v20. The results obtained between the parameters are summarized in the Table 4. According to (Cohen 1988, 1992), the correlation coefficients 0.1, 0.3 and 0.5 will refer to weak, , moderate and strong correlation respectively, while correlation coefficients, 0.0 and 1.0 will refer to “no correlation” and “perfect correlation” respectively.

The study reveals a large correlation between the Fuzzy Upper New-Generation whole-life cost model and the Classical New-generation whole-life cost model, while there is a perfect correlation between the standard whole-life cost model and the fuzzy lower new generation whole. Based on Cohen’s result, it could also be argued that a moderate correlation exists between the fuzzy mean new-generation whole-life cost and the classical new-generation whole-life cost. The results between the fuzzy lower new-generation whole-life cost and the fuzzy mean new generation whole-life cost were not statistically significant. Equally, the agreement between the Fuzzy Mean new-generation whole-life cost and the Standard Whole-life Cost model were not statistically significant. This implies that the standard and the classical new-generation whole-life cost model are only distinguishable as two models based on the considerations of probabilistic uncertainty. Using fuzzy set to model the whole-life cost of buildings will however eliminate the need to use two different models as the fuzzy new-generation whole-life cost model adequately provides a range of estimates for the whole-life costs of buildings which correlates with the standard whole-life cost and the new-generation whole-life cost values. Equally, the fuzzy set mechanism provides an approach that reveals the variability in the whole-life cost values of buildings for respective configurations, over the expected life. Hence, fuzzy set theory can be seen as a robust and sufficient means for modelling uncertainty in whole-life costing.

7 CONCLUSION

Whole-life costing of buildings plays a significant role in assessing the optimal combination of feasible options in the conceptual stage of a building. There are different approaches to the estimation of the whole-life cost of buildings, this approach principally differ in the treatment of uncertainty in the model framework. The new-generation whole-life cost model is a mathematically tractable and intellectually stimulating approach to whole-life costing. However, it is based on a rigid probabilistic mechanism. This work explores the use of fuzzy set theory to model the uncertainty in the cashflow values over the life of a building and correlates the result with existing techniques.

This work reveals a perfect correlation between the standard whole-life cost model and the fuzzy lower new-generation whole-life cost model. Equally, there is a strong correlation between the new-generation whole-life cost model and the fuzzy upper new-generation whole-life cost model. This revels that fuzzy set theory is a robust framework to estimate the whole-life cost of buildings as it provides a sufficient and viable template for modelling the whole-life cost of buildings.

It is however instructive that a single-point whole-life cost estimate might be misleading for construction clients requiring conclusive guidance on the most economical option over the life of their built. Hence the range of values provided by fuzzy set theory is beneficial for construction clients in making more rational decision choices in selecting the optimal choice over the estimated life of the building.

Further work will involve the development of an elaborate questionnaire to test which of the models best estimates the whole-life cost of buildings over the estimated life. This procedure will therefore provide an empirical justification for the models in practice and will help to answer whether a “whole” is not simply the “sum of its part”. The Greek Philosopher- Aristotle argues that the “whole” is more! Further work will therefore test this hypothesis in subsequent studies.

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