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Characteristic and allowable compressive strengths of *Dendrocalamus Sericeus* bamboo culms with/without node using artificial neural networks

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A R T I C L E I N F O

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Compressive strength prediction
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Indicative properties
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Allowable strength

A B S T R A C T

The strength of construction material is a crucial consideration in the process of structural design and construction. Conventional materials such as concrete or steel have been widely utilized due to their predictable material performance. However, a significant obstacle to the widespread use of bamboo in structural elements lies in the challenge of its standardization. Many previous research studies have explored bamboo's load bearing capacity, but the information remains limited due to variations in species, size, age, physical properties, moisture content, and other factors, making it difficult to predict their load-bearing capacity. This study aims to propose Artificial Neural Network (ANN) models to predict ultimate compressive load and compressive strength of *Dendrocalamus Sericeus* bamboo culm. Additionally, for structural design purposes, the proposed ANN models were employed to determine the characteristic and allowable compressive strengths. As a first step, experimental data from compressive tests in the literature were used for training and developing the ANN model. To investigate the effect of the node on compressive loading capacities, the test data were separated into two datasets, "Node" samples and "Internode" samples. Through the training process, ANN models were finally proposed, and the R-square values for the prediction of ultimate compressive load and compressive strength from the proposed ANN models were significantly higher than those obtained from the linear regression analyses used in the literature. Subsequently, the characteristic and allowable compressive strengths were calculated and compared to the strengths obtained from the experiment data, revealing a difference of approximately only 8.0%. Overall, the ANN models presented in this study offer promising predictive ability for both ultimate compressive load and compressive strength of *Dendrocalamus Sericeus* bamboo culm, as well as for determining characteristic and allowable strengths. Hence, ANN models are suggested to be adopted as a tool for the design and construction of bamboo buildings.

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1. Introduction

Climate change has grown to be a serious topic in recent years resulting in its associated negative effects on the environment. Currently, the use of modern construction materials has been identified as a major cause of pollution, including air and water pollution. As such, the building industry has been identified as having significant potential to reduce global warming [1]. Raising awareness about the use of natural substitute materials is crucial in order to reduce these pollutants moving forward. To illustrate, cement production consumes 10.5 EJ of world energy and contributes to about 5% of global CO_2 emissions [2]. Hence, the search for sustainable building materials, particularly in the realm of bio-based materials [3], has become essential and of great interest in the field of Engineering.

Bamboo offers environmental advantages over traditional building materials such as steel and concrete due to its reduced Global Warming Potential (GWP) [4,5]. Among various natural substitutes, bamboo grows rapidly and can be harvested and replanted with minimal environmental impact [6]. Bamboo, a monocotyledon grass, is known for having the longest stems found in tropical areas. Currently, there are 1662 bamboo species, divided into 121 genera. Many developing countries, especially in Asia, heavily rely on bamboo for economic support. In Thailand, a Southeast Asian country, there are 15 genera and 80 species of bamboo [7]. Bamboo has been used as a building material for thousands of years due to its mechanical characteristics that are suitable for structural applications. These include a high strength-to-weight ratio, flexibility of the fibrous microstructure. Bamboo stands out as a material with excellent mechanical properties that can serve as a substitute for traditional construction materials [8]. Considering both its mechanical properties and its availability for plantation, bamboo-based houses can be used as multi-hazard disaster-resistant residences [9–12].

Based on the various potentials of bamboo, there has been extensive research conducted on the mechanical properties of bamboo within the research community. For instance, Shao et al. [13] conducted a study on *Moso* bamboo's tensile characteristics, specifically quantifying the fluctuation of fiber area across the radial thickness of the internodes. They determined the tensile strength and elastic modulus of the fiber bundles to be approximately 480 MPa and 34 GPa, respectively. Regarding the moisture absorbability of the bamboo, Amiruddin et al. [14] investigated the influence of water content on bamboo's tensile strength. Their findings revealed that the tensile strength of bamboo increases as the water content decreases. Richard [15] conducted flexure experiments to evaluate the longitudinal shear capacity of bamboo culms for structural applications, while Nugroho and Bahtiar [16] altered the culm shape to examine the fundamental characteristics of tapered bamboo. Each bamboo species possesses distinct properties. In their study, Chaowana et al. [7] examined how bamboo species and culm size—specifically, the outer culm diameter and culm wall thickness—impact the characteristics and properties of various species: *Dendrocalamus asper*, *Dendrocalamus sericeus*, *Dendrocalamus membranaceus*, *Thyrsostachys oliveri*, and *Phyllostachys makinoi*. Kenneth and Uzodimma [17] investigated the influence of nodes and other physical parameters on the compressive strength of *Guadua angustifolia* (Colombian Timber Bamboo) culms. They found that the mechanical properties of bamboo are significantly influenced by its physical properties.

The studies listed above show that bamboo has remarkable mechanical qualities that can be used in a variety of engineering applications. However, building with bamboo is not straightforward. Hailemariam et al. [18] conducted a study on the barriers, benefits, and opportunities of employing bamboo materials for structural purposes. A significant obstacle to the widespread use of bamboo in structural elements lies in the challenge of standardization. Given bamboo's natural origins, it's engineering properties, shapes, sizes, and so forth, remain uncertain. Considering these factors and their impact on strength, determining the load-bearing capacity in the design stage and upholding quality control during construction become pivotal.

The material testing standard ISO 22157–1:2019 [19] outlines test procedures for physical properties such as density, moisture content, shrinkage, as well as load-bearing capacities including compression, bending, shear, and tension. Since all the physical properties mentioned above are uncontrollable and can impact load-bearing capacities, conducting experiment to determine these capacities can be time-consuming and costly. Therefore, ISO 19624:2018 [20] defines indicative properties, which are non-destructive measurements used to estimate the mechanical properties of bamboo. This approach facilitates easier measurement, potentially streamlining the testing process and saving time. Common indicative bamboo properties encompass moisture content, node and internode inclusion, density, culm wall thickness, diameter, and linear mass, all of which can influence strength [21,22]. In the work of Tangphadungrat et al. [23], compressive load tests were conducted on *Dendrocalamus sericeus* Munro bamboo culms, employing both simple linear and multiple linear regression to establish relationships between significant indicative properties and the responses.

An artificial neural network (ANN) model is a computational model inspired by the structure and functioning of the human brain. It is a type of machine learning algorithm that is used for pattern recognition, data analysis, and decision-making tasks. It is particularly well-suited for tasks that involve large amounts of data and complex patterns. This approach has been adopted in various engineering fields, especially when the application of theoretical-based formulas is overly complicated. For instance, when evaluating a range of machine learning models for predicting the compressive strength of concrete and mortar, it is evident that artificial neural networks (ANNs) can effectively and reliably predict compressive strength in both concrete and mortar, as seen in references [24–29]. However, its application in the modeling of mechanical responses of bamboo has been very limited [30], which is the focus of this study.

Dendrocalamus sericeus Munro bamboo is a bamboo species widely used as a building material [31]. Furthermore, the Royal Project Foundation in Thailand has actively promoted its cultivation for culm production, creating market opportunities and production potential in the region [7]. This work utilized an experimental dataset of *Dendrocalamus sericeus* Munro bamboo from the previous research [23] aimed at developing Artificial Neural Network (ANN) models for predicting compressive strengths based on indicative nondestructive properties. The improvement in the accuracy of the ANN models for predicting compressive strengths was compared with the regressed formulas [23]. The ultimate goal of this research is to provide a tool to assist in structural design. Therefore, the

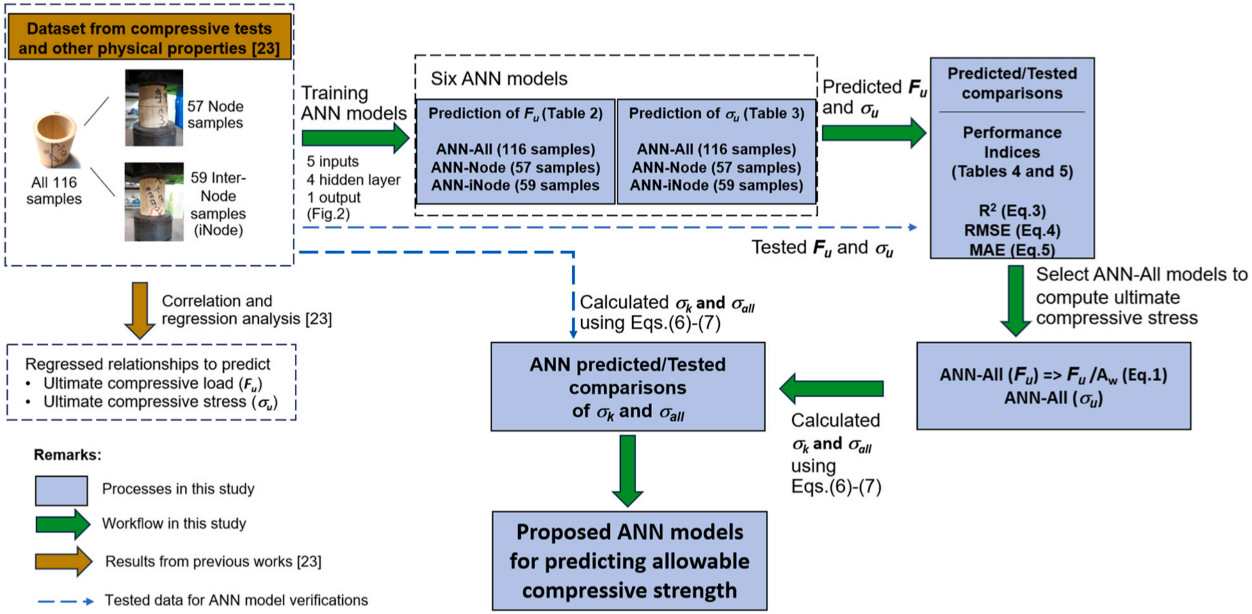


Fig. 1. Development of ANN models for predicting the characteristic and allowable compressive strengths of *Dendrocalamus sericeus Munro* bamboo.

proposed ANN models were further employed to determine the characteristic and allowable compressive strengths. Consequently, with the ability to predict strength more reliably, the findings of this study offer a valuable framework for designing bamboo structures and implementing quality control within the bamboo construction industry.

2. Theory and method

The compression tests dataset used for developing the ANN models was obtained from the authors' previous research [23]. Tangphadungrat et al. [23] conducted the compression tests on *Dendrocalamus sericeus Munro* bamboo culms to determine their compression load capacity and strength, following ISO 22157–1:2019 [19] guidelines. In this current study, the distribution of the tested data was re-examined, and the experimental results were used to train ANN models to predict the ultimate compressive load capacity (F_u) and strength (σ_u) based on most correlated indicating properties (IP). Next, the proposed ANN models were used to generate a new set of ultimate compressive strength data and compared with the tested results to examine the accuracy of the proposed models. Allowable strength is a crucial design parameter, rather than the ultimate strength, for determining structural member dimensions and acceptable safety margins. Hence, the dataset generated by selective ANN models (ANN-All model) was further employed to determine the characteristic and allowable compressive strengths, following ISO 22156:2021 [32] guidelines. Finally, a comparison was made between the results of characteristic compressive strength and allowable compressive strength obtained from the tests and those predicted by the selected ANN models. The methodology for developing the ANN models is outlined in Fig. 1. This analysis aimed to assess the suitability of using ANN models for predicting the allowable compressive strength of *Dendrocalamus sericeus* Munro bamboo.

2.1. Non-destructive tests, compressive tests and their correlation

2.1.1. Non-destructive tests

One hundred and sixteen pieces of *Dendrocalamus sericeus* bamboo taken from 39 culms, each from different parts; top, middle, and bottom portions, and were used as test specimens. For each specimen, dimensions and weight were measured and the following non-destructive properties were recorded [23]:

1. Moisture content (M_c)
2. The measured properties that reflect "fiber densities" as the volumetric density (ρ) and linear mass (q) in different conditions
   21. air-dried (ρ_a and q_a),
   22. oven-dried (ρ_o and q_o),
   23. 12% moisture content (ρ_{12} and q_{12})

2.1.2. Compressive test

The compressive testing to failure was conducted to determine the maximum compression load (F_u). Subsequently, the compressive strength (σ_u) was calculated by dividing the maximum compressive load with its cross-sectional area (A_w) using Eq. (1),

$$\sigma_u = \frac{F_u}{A_w} = \frac{4F_u}{\pi\left(D^2 - (D - 2t)^2\right)} \tag{1}$$

The maximum compressive load (F_u) and compressive strength (σ_u) are mathematically related through the sectional area. In the case of a homogeneous material, the two values are identical in terms of the compressive capacity. However, different parts of bamboo culms, even with the same cross-sectional area, may exhibit different physical properties. Therefore, both loading capacities are typically considered in structural design.

2.2. Correlation analysis

The non-destructive properties were statistically analyzed to determine their correlation coefficient with the strength. The coefficient derived from this analysis helps in identifying the non-destructive properties that can serve as "indicative properties" for strength prediction. In this study, the Pearson correlation coefficient (r) served as a statistical indicator to assess the mutual connection between the non-destructive indicating properties and the compressive capacities (F_u and σ_u). The correlation coefficient takes on values between -1 and $+1$, where values near -1 or $+1$ indicate a perfect correlation, and 0 indicates no correlation. A positive correlation implies that both values move in the same direction, whereas a negative correlation indicates opposite directions of movement [33].

2.3. Artificial neural network models

Artificial neural networks (ANNs) are sophisticated data processing systems based on the human brain system. ANNs are composed of nodes or neurons, all interconnected with connection links, and each having its weight. Each neuron captures a weighted sum of inputs, and passes it through an activation function to compute the provisional value of an output. This process is called feed-forward. Subsequently, gradient descent and backpropagation are employed to adjust the values of the weights in each link until the errors

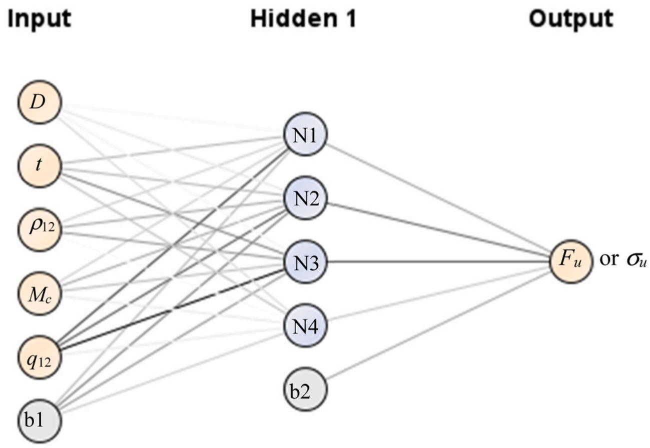


Fig. 2. Proposed ANN models to predict bearing capacities of bamboo culm.

between the output obtained from feed-forward process and output from dataset are minimized.

The experimental results conducted on *Dendrocalamus Sericeus* bamboo culms [23] in Section 2.1 were utilized to develop Artificial Neural Network (ANN) models for predicting the compressive load capacity (F_u, kN) and compressive strength (σ_u, MPa). These ANN models were designed with three layers: an input layer, a hidden layer, and an output layer, as illustrated in Fig. 2. The total number of experimental samples in this work is more than ten times the quantity of input variables, ensuring the feasibility of building a prediction model [28].

In the feed-forward process, as stated previously, each neuron receives inputs from the previous layer, and the weighted sum of those inputs is computed. An activation function is then used to create outputs for the next layer. To compute the weighted sum of inputs for the current *j*-th neuron, the set of *n*-inputs, denoted as $X = (x_1, x_2, \ldots, x_n)$, is multiplied by the weight vector $W_j = (w_{j1}, w_{j2}, \ldots, w_{jn})$, and the biases ($b_j$) are added, as shown in the following equation:

$$Y_j = \sum_{i=1}^{n} w_{ji} x_i + b_j \tag{2}$$

where Y_j is the weighted sum of outputs before being sent to the activation function.

Through Pearson correlation analysis, as explained in Sections 2.2 and 3.1, it was determined that five indicating properties exhibited significant correlations with the compressive strengths [23]. These indicative properties include outside diameter (D, mm), wall thickness (t, mm), density at 12% moisture content (ρ_{12}, kg/m^3), percent of moisture content (M_c), and linear mass at 12% moisture content (q_{12}, kg/m). Hence, the input layer contained 5 neurons, each representing the indicating properties (IP) properties that were correlated with the strengths, and one bias neuron (b1).

The hidden1 layer comprised a total of 4 neurons (N1 to N4) and one bias neuron (b2). The compressive load capacity (F_u) or compressive strength (σ_u) values were represented in a single output layer. Neurons in consecutive layers were interconnected through weights. The output layer encompassed one neuron responsible for generating the network's prediction of F_u and σ_u. The models were trained through iterations with specified momentum rate and learning rate until the error, calculated from the ANN predicted values and experimental results, was minimized.

Three frequently used performance indicators, such as the square correlation coefficient (R^2), root mean squared error (RMSE), and mean absolute error (MAE), are employed to analyze the performance of selected ANN models. The higher R^2 value, closer to 1, indicates a strong correlation between predicted values and actual values. Conversely, lower values (closer to zero) of RMSE and MAE suggest the better the performance of the selected models. Eqs. (3)–(5) [24–29] provide the relevant expressions for R^2, RMSE, and MAE, respectively:

$$R^2 = \frac{\left[\sum_{i=1}^{n} (E_i - \overline{E})(P_i - \overline{P})\right]^2}{\sum_{i=1}^{n} (E_i - \overline{E})^2 \sum_{i=1}^{n} (P_i - \overline{P})^2} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (E_i - P_i)^2}{n}} \tag{4}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |E_i - P_i| \tag{5}$$

Here n is the number of samples in the datasets, E_i is the ith experimental value, $\overline{E}$ is the mean value of experimental data, and P_i is the ith predicted value corresponding to E_i, and $\overline{P}$ is the mean of predicted values.

Table 1
Five non-destructive indicating properties and compressive capacities.

Properties	Min	Max	Mean	SD	Skewness	Kurtosis
Part 1. Five non-destructive indicating properties						
Culm wall thickness (t, mm.)	6.779	27.028	12.886	4.528	0.941	0.311
External diameter (D, mm.)	74.603	109.290	89.821	8.013	0.739	0.330
Moisture content (M_c, %)	11.071	19.702	13.720	2.089	0.976	-0.077
Density at 12%Mc (ρ_{12}, kg/m^3)	544.158	1121.518	834.469	123.926	0.214	-0.212
Linear mass at 12%Mc (q_{12}, kg/m)	1.053	4.251	2.514	0.712	0.443	-0.458
Part 2. Compressive capacities						
Maximum compressive load (F_u, kN)	71.982	256.934	167.342	41.755	0.132	-0.821
Maximum compressive strength (σ_u, MPa)	36.233	71.923	55.979	8.094	-0.358	-0.579

2.4. Allowable compressive strength

Classical approaches encompass Allowable Stress Design (ASD) and Ultimate Strength Design (USD). However, with the development of predictive models, Performance-Based Design (PBD) has emerged as an alternative for structural design. To prevent brittle failure modes under extreme loads, like accidental loads, car crash, impact loads or earthquakes [34–36], the capacity design philosophy [37] has found application. Yet, due to limitations in information about the material nonlinearity of bamboo, the ASD design method has been widely adopted.

For the ASD design method, an allowable strength is employed in engineering design to represent the maximum stress or load that a structural component can withstand while still meeting safety requirements and design criteria. This strength value is calculated by dividing the ultimate strength of a material by a safety factor, which considers uncertainties in material properties, manufacturing processes, and loading conditions. Various factors, including species, age, and harvesting methods, influence bamboo's allowable strength. Therefore, it is crucial to utilize reliable and relevant data concerning the strength properties of the specific bamboo species in use. According to ISO 22156:2021 [32], the expression for the allowable design strength is as follows:

$$\sigma_{all} = \frac{C_R C_{DF} \sigma_k}{FS} \approx 0.248\sigma_k \tag{6}$$

where σ_{all} represents the allowable design strength, σ_k denotes the 5th percentile characteristic strength with 75% confidence, C_R is the member redundancy factor; for load-bearing members $C_R = 0.90$, C_{DF} is the modification factor for service class and load duration; for permanent and long term applied load with service class 2 $C_{DF} = 0.55$, FS is the material factor of safety; for compressive load $FS = 2.0$. The 5th percentile characteristic strength with 75% confidence in Eq. (6) is computed as follows,

$$\sigma_k = \sigma_{0.05}\left(1 - \frac{2.7s}{m\sqrt{n}}\right) \tag{7}$$

where $\sigma_{0.05}$ is the 5th percentile from the test data, m is the mean value from the test data, s is the standard deviation from the test data, and n is the number of tests. The 5th percentile from the test data in Eq. (7) is calculated from one tail student's t-distribution with the number of degrees of freedom equal to n minus one, i.e.

$$\sigma_{0.05} = m - s\left|t_{0.05,n-1}\right| \tag{8}$$

Note that the t-distribution values in Eq. (8) was approximated to 1.645 assuming the number of samples were very large, as proposed in Kaminski et al. [38]. Alternatively, the 5th percentile value of bamboo strength can be directly obtained from tested data.

3. Results

3.1. Experimental data: non-destructive indicating properties and compressive tests

The correlation between the non-destructive qualities and capacities of *Dendrocalamus sericeus* Munro bamboo was investigated by Tangphadungrat et al. [23]. The linear mass, with a Pearson correlation coefficient ranging from 0.884 to 0.894, showed the strongest positive association with the maximum compressive load (F_u). Following this, culm wall thickness (t), outer diameter (D), and moisture content (M_c) were listed in decreasing order. Other variables had moderate, weak, or negligible correlations with the capacity. The maximum compressive load was expected to increase as these aforementioned qualities improved. Density (ρ_{12}), with a Pearson correlation coefficient of 0.556–0.616, exhibited the strongest association with the maximum compressive strength (σ_u) among all indicative metrics. Also of high relevance, though with a negative correlation (−0.602), was the culm wall thickness.

Table 1 presents the outcomes of five non-destructive indicating properties from the 116 tests. Fig. 3 displays the data frequency distribution of the indicative properties and compressive test capacities. Skewness and Excess Kurtosis (referred to as "Kurtosis") are metric measuring the distribution's asymmetry and tailedness concerning a normally distributed population. Skewness and kurtosis values of zero indicate perfectly normal distribution of observed data. As shown in Table 1, all variables' skewness ranges from − 0.462 to 0.976, and kurtosis ranges from − 0.821 to 0.330. Thus, the recorded data distributions exhibit an acceptable level of normality

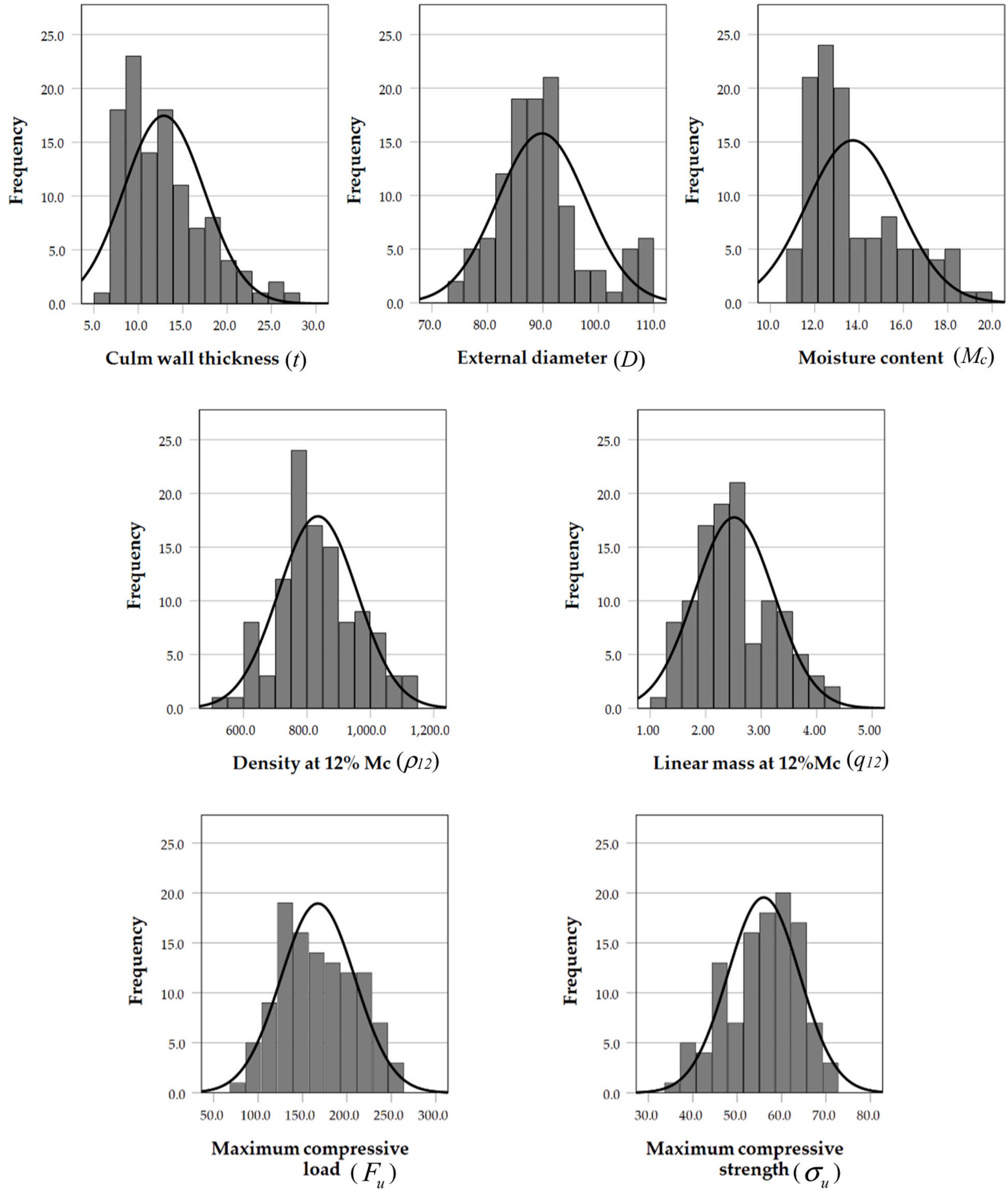


Fig. 3. Histogram of the indicating properties and compressive capacities.

(values between ±1 are considered perfect, < ± 2 are deemed acceptable [39]).

3.2. Development of neural network models

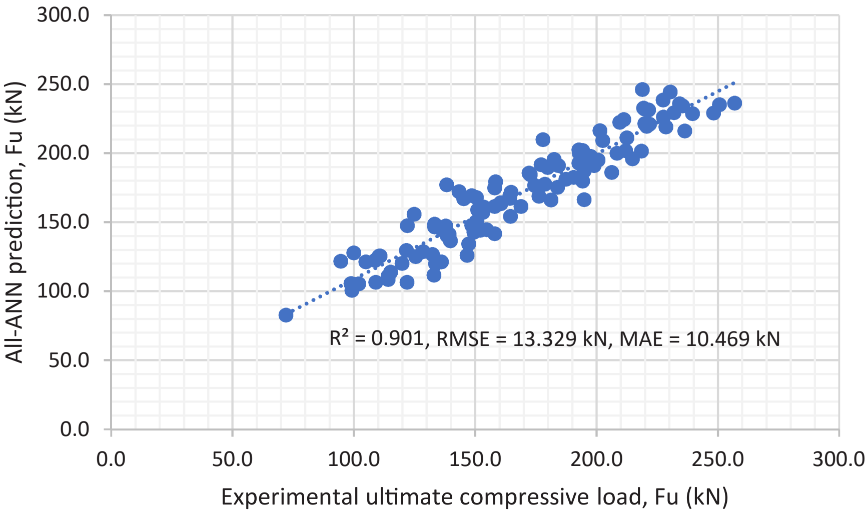
In Fig. 2, all the hidden and output neurons have their biases. The biases and weights of each link are adjusted via the back-

Table 2
The values of weight and bias of ANN models to predict the ultimate compressive load.

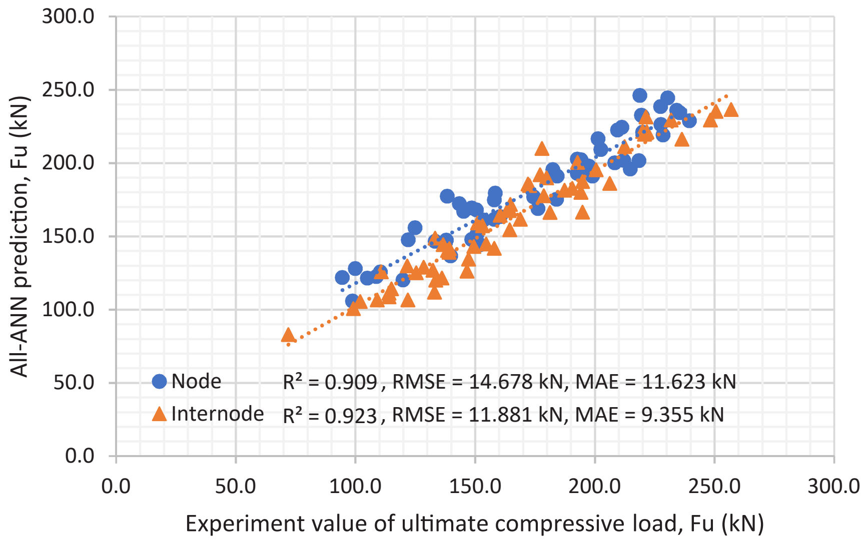
Input, IP/Output, F_u	**Hidden node: N1**			**Hidden node: N2**			**Hidden node: N3**			**Hidden node: N4**			Bias, b2		
	All	**Node**	**iNode**	**All**	**Node**	**iNode**	**All**	**Node**	**iNode**	**All**	**Node**	**iNode**	**All**	**Node**	**iNode**
Input 1, D	0.043	-0.075	0.119	-0.187	0.321	-0.122	0.065	0.235	0.167	0.263	0.201	-0.000	-	-	-
Input 2, t	0.565	0.592	0.150	0.556	0.289	-0.572	0.970	1.000	0.474	0.455	0.228	0.155	-	-	-
Input 3, ρ_{12}	-0.343	-0.072	0.204	-0.682	-0.795	-0.091	-0.817	-0.519	0.008	-0.011	-0.011	-0.212	-	-	-
Input 4, M_c	-0.355	-0.460	-0.236	0.673	0.438	-0.044	-0.520	-0.623	-0.045	0.150	0.045	0.242	-	-	-
Input 5, q_{12}	1.548	1.599	0.700	-1.345	-1.091	-1.383	2.155	2.253	1.206	0.153	0.333	-0.112	-	-	-
Bias, b1	0.536	0.859	0.191	-0.994	-0.852	-1.244	0.818	1.033	0.742	-0.384	-0.202	-0.184	-	-	-
Output, F_u	0.700	0.912	0.601	-1.220	-1.305	-1.458	1.356	1.534	1.021	-0.438	-0.263	-0.380	-0.690	-0.895	-0.241

Table 3
The values of weight and bias of ANN models to predict the compressive strength.

Input, IP/ Output, σ_u	Hidden node: N1			Hidden node: N2			Hidden node: N3			Hidden node: N4			Bias, b2		
	All	**Node**	**iNode**	**All**	**Node**	**iNode**	**All**	**Node**	**iNode**	**All**	**Node**	**iNode**	**All**	**Node**	**iNode**
Input 1, D	0.111	-0.036	-0.510	-0.142	-0.057	-0.199	0.145	0.230	0.608	0.536	0.765	-0.507	-	-	-
Input 2, t	0.112	-0.104	0.029	0.151	0.029	0.050	0.137	0.277	0.336	0.583	0.293	0.440	-	-	-
Input 3, ρ_{12}	0.459	0.966	0.919	0.359	0.247	0.352	0.039	-0.120	-0.446	-2.672	-1.474	-1.958	-	-	-
Input 4, M_c	-1.790	-0.942	0.252	-0.582	-0.124	0.211	0.332	0.265	0.265	0.489	0.341	0.740	-	-	-
Input 5, q_{12}	-0.044	0.524	-0.114	0.077	0.227	-0.001	-0.075	0.207	0.308	-0.367	-0.861	-0.386	-	-	-
Bias, b1	-1.749	-0.665	-0.456	-1.190	-0.422	-0.515	-0.943	-0.410	-0.544	-1.618	-0.782	-1.154	-	-	-
Output, σ_u	1.233	1.194	0.856	0.475	0.293	0.337	-0.029	-0.246	-0.677	-1.548	-1.514	-1.797	-0.156	0.001	0.131



(a) All samples



(b) Separated node and internode samples

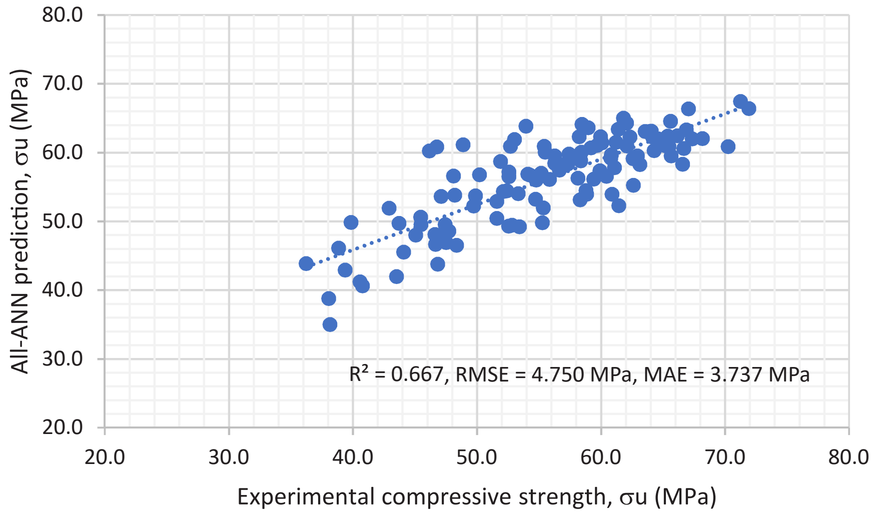
Fig. 4. Experimental results versus predicted results (All-ANN) of ultimate compressive load.

propagation process until the sum-square error reaches an extremely small value. The sigmoid activation function is used in all neurons in the hidden layer, while a linear activation function is employed in the output layer. The optimal values of weights and biases used in the ANN models to predict compressive load capacity and compressive strength are shown in Tables 2 and 3. The number of nodes in the hidden layer and the number of hidden layers are chosen through trial-and-error to obtain the minimum value of the sum-square error. It is noted that all 116 bamboo culm samples are separated into two groups: 57 "node" samples and 59 "internode" (without node) samples. Therefore, three cases of the training process are defined based on the data used: (1) all samples, (2) only node samples, and (3) only internode samples (iNode). Hereinafter, for the sake of clear explanation, the models are represented as the All-ANN model, Node-ANN model, and iNode-ANN model, respectively.

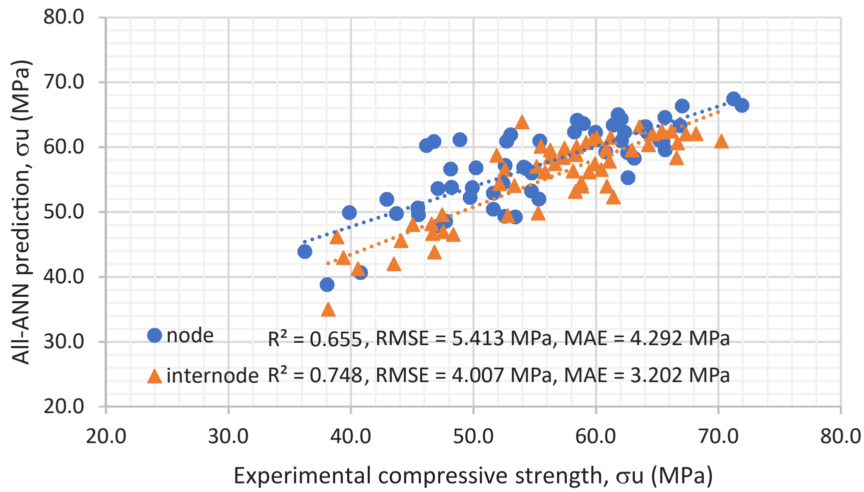
3.3. Compressive strength comparisons: test and ANN models

3.3.1. All-ANN models

To demonstrate the accuracy of the All-ANN model (trained with all data, including node and internode samples) in predicting the compressive capacity of bamboo culms, the squared correlation (R^2) between the predicted and tested values of ultimate compressive load and compressive strength, as well as the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), were determined. The



(a) All samples



(b) Separated node and internode samples

Fig. 5. Experimental results versus predicted results (All- ANN) of compressive strength.

Table 4
Prediction performance indices for predicting ultimate compressive load of bamboo culm (F_u).

Model	R^2			RMSE (kN)			MAE (kN)		
	All sample	Node sample	iNode sample	All sample	Node sample	iNode sample	All sample	Node sample	iNode sample
All-ANN	0.901	0.909	0.923	13.329	14.678	11.881	10.469	11.623	9.355
Node-ANN	0.859	0.927	0.922	19.511	11.564	24.886	16.074	9.378	22.544
iNode-ANN	0.827	0.900	0.929	19.025	24.314	11.883	14.583	20.761	8.614
*__SLR__ [23]	0.800	0.868	0.910	NA	NA	NA	NA	NA	NA
**__MLR__ [23]	0.861	NA	NA	NA	NA	NA	NA	NA	NA

* SLR: $F_u = 52.433q_{12} + 35.522$ (Allsample)$F_u = 58.444q_{12} + 6.363$ (Node)$F_u = 60.917q_{12} + 27.206$ (Internode)
** MLR: $F_u = 3.413t + 0.383D - 5.834M_c + 44.301q_{12} + 57.593$

scatter plots of tested versus predicted values for ultimate compressive load capacity and strength are presented in Figs. 4(a) and 5(a), with the corresponding R^2, RMSE and MAE, shown in each plot. The values of R^2, RMSE, and MAE for ultimate compressive load capacity are 0.901, 13.329 and 10.469, respectively. They are 0.667, 4.750, and 3.737 for compressive strength.

Table 5
Prediction performance indices for predicting compressive strength of bamboo culm (σ_u).

Model	R^2			RMSE (MPa)			MAE (MPa)		
	All sample	Node sample	iNode sample	All sample	Node sample	iNode sample	All sample	Node sample	iNode sample
All-ANN	<u>0.667</u>	0.655	0.748	<u>4.750</u>	5.413	4.007	<u>3.737</u>	4.292	3.202
Node-ANN	0.437	<u>0.732</u>	0.656	7.654	<u>4.610</u>	9.729	6.280	<u>3.721</u>	8.752
iNode-ANN	0.564	0.611	<u>0.808</u>	6.066	7.907	<u>3.456</u>	4.532	6.319	<u>2.806</u>
*SLR[23]	0.380	0.651	0.692	NA	NA	NA	NA	NA	NA
**MLR[23]	0.597	NA	NA	NA	NA	NA	NA	NA	NA

* SLR: $\sigma_u = 0.040\rho_{12} + 22.389$ (Allsample)$\sigma_u = 0.063\rho_{12} - 1.778$ (Node)$\sigma_u = 0.076\rho_{12} - 1.531$ (Internode)
** MLR: $\sigma_u = -0.089t - 1.683M_c + 0.036\rho_{12} + 50.435$

To examine the effect of node inclusion on the compressive capacity, all test results were divided into two groups: one with node samples and another with internode (without node) samples. Figs. 4(b) and 5(b) illustrate the R^2, RMSE and MAE for the prediction of ultimate compressive load and compressive strength of these separated groups of specimens. As shown in Figs. 4(b) and 5(b), the $R^2$of predictions for internode samples is higher than that of node samples, but the RMSE and MAE are smaller. In other words, the presence of nodes in bamboo culms does not significantly affect their compressive capacities, but it may lead to variations in the capacity determination.

To demonstrate the improvement of the proposed All-ANN models, the squared correlations are compared with the regressed relationships presented in the previous work by Tangphadungrat et al. [23], as shown in Tables 4 and 5. The R^2 correlations of the ANN predictions are notably higher than the predictions of the bearing capacity of bamboo culm obtained from simple linear regression (SLR) and multi-linear regression (MLR) analyses. It is important to note that the R^2 values for SLR and MLR are taken from the most accurate model in the work of Tangphadungrat et al. [23]. The R^2 values presented in Tables 4 and 5 clearly indicate that the proposed ANN model is more accurate in predicting the ultimate compressive load and compressive strength of bamboo culm compared to the SLR and MLR models. The improved accuracy of the ANN models makes it a more reliable and effective approach for these predictions.

NA: in Ref. [23], RMSE and MAE were not determined, and MLR used all samples for modelling.

The underlined values are the prediction performance indicators with a consistent training dataset.

NA: in Ref. [23], RMSE and MAE were not determined, and MLR used all samples for modelling.

The underlined values are the prediction performance indicators with a consistent training dataset.

3.3.2. Separated training of Node-ANN and iNode-ANN models

The values of R^2, RMSE and MAE for the separated Node-ANN model and iNode-ANN model, predicting ultimate compressive load and compressive strength, are shown in Tables 4 and 5, respectively. Using the separately trained ANN models to predict the strength of the consistent data results in an improvement of all performance indicators: R^2, RMSE and MAE. For example, the R^2 values obtained from the Node-ANN model to predict the ultimate compressive load and compressive strength of the consistent "node" samples are 0.927 and 0.732, respectively. These values are enhanced from 0.909 and 0.655 predicted by the All-ANN model. Similarly, using the iNode-ANN model to predict ultimate compressive load and compressive strength of the consistent "internode" samples yields values of 0.929 and 0.808, respectively. As expected, the performance of the separately trained models, such as the Node-ANN model or iNode-ANN model, is lower in predicting the ultimate compressive load and compressive strength of all samples or inconsistent samples than those of the predicted values using the All-ANN or a consistent ANN model.

4. Allowable compressive strength using ANN models

As the cross-sectional area of a bamboo culm is not uniform, using compressive strength (σ_u) is more versatile in designing a bamboo structure than ultimate compressive load (F_u). To be useful for the structural design purpose, the values of allowable compressive strength was determined based on the ultimate compressive strength (σ_u). To illustrate the applicability of the proposed ANN models, All-ANN models were adopted to determine the characteristic and allowable strengths. The All-ANN model was selected due to it's covering all types of culms ignoring the presence of nodes, which reflects the real practice of using bamboo as a structural element. Using the All-ANN models, the compressive strength (σ_u) can be computed either from the predicted ultimate compressive load (F_u), divided by the specimen section area according to Eq. (1), or directly from the predicted compressive strength (σ_u). Then predicted ultimate strengths, as well as the ultimate strength from the experiment [23], were calculated for the characteristic compressive strength (σ_k) and allowable compressive strength (σ_{all}) using Eqs. (6)–(8). Table 6 shows the characteristic compressive strength and allowable compressive strength of the experiment in Column 1. Columns 2 and 3 indicate the allowable strengths from the predicted models. From Table 6, the characteristic and allowable compressive strengths obtained from the All-ANN models have an error compared to the experimental data of approximately only 8%.

Table 6
Characteristic and allowable compressive strengths from experiment versus ANN models.

Compressive Strength	1. Experiment (MPa)	2. All-ANN1 (MPa)	3. All-ANN2 (MPa)	(1/2) Error (%)	(1/3) Error (%)
Mean value	55.6	56.4	56.2	1.4	1.1
Standard deviation	8.22	6.80	6.64	-	-
σ_kEq. (7)	40.5	43.8	43.8	8.2	8.2
σ_{all}Eq. (6)	10.0	10.8	10.8	8.0	8.0

*Col.#1. Experiment: test data, Col.#2. All-ANN1: ALL-ANN predicted ultimate compressive load divided by specimen cross-section area, Col.#3. All-ANN2: ALL-ANN directly predicted ultimate compressive load

5. Conclusions

In this study, experimental data from one of the author's previous works [23], which included ultimate compressive tests of *Dendrocalamus Sericeus* bamboo culms, were utilized. These data served here as the foundation for developing ANN models aimed at predicting ultimate compressive load (F_u) and compressive strength (σ_u). All test data was categorized into two groups: "node" samples and "internode" sample. Consequently, the training data were split into "All dataset", "node dataset" and "internode dataset". This process resulted in the development of a total of six ANN models, each designed to cover the three dataset types and two strength types. These models are named All-ANN, Node-ANN, and iNode-ANN, respectively, and are used for predicting F_u and σ_u. The accuracy of the proposed ANN models was assessed using three performance indices: the squared correlation (R^2), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

Based on the prediction performance indices (R^2, RMSE and MAE), using the separately trained ANN models to predict the strength of the consistent data led to an improvement in all performance indicators. In contrast, the performance of the separately trained models, such as the Node-ANN model or iNode-ANN model, was lower in predicting the ultimate compressive load and compressive strength of all samples or inconsistent samples compared to the predicted values using the All-ANN or a consistent ANN model.

When comparing the predictions with the previous work using the simple and multiple linear regression analyses [23], the proposed ANN models exhibited higher R^2 values. Consequently, the developed ANN models offer significant improvement in predicting the ultimate compressive load and ultimate compressive strength.

Many past research studies have focused on predicting the ultimate strength. However, rather than using ultimate strength, allowable strength is a crucial design parameter for structural engineers to determine the structural dimensions and building safety. Therefore, the proposed All-ANN models, for example, were adopted to determine the ultimate compressive strengths and further calculate the characteristic and allowable compressive strengths. The values were compared to the strengths obtained from the experiment data, with a difference of approximately 8.0%.

In sum, the ANN models presented in this study offer promising and improved predictions for both ultimate compressive load and compressive strength of *Dendrocalamus Sericeus* bamboo culm, outperforming traditional linear regression methods. Furthermore, they are applicable for determining allowable strength. As a result, the models are suggested to be adopted as a tool for the design and construction of bamboo buildings.

CRediT authorship contribution statement

Chinnapat Buachart: Methodology, Data curation, Writing – review & editing. **Chayanon Hansapinyo**: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition, Project administration. **Piti Sukontasukkul**: Supervision, Writing – review & editing. **Hexin Zhang**: Supervision, Writing – review & editing. **Worathep Sae-Long**: Supervision, Writing – review & editing. **Panatchai Chetchotisak**: Supervision, Writing – review & editing. **Timothy E. O'Brien**: Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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