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Prediction Model for Mechanical Properties of Lightweight Aggregate Concrete Using Artificial Neural Network

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Abstract: The mechanical properties of lightweight aggregate concrete (LWAC) depend on the mixing ratio of its binders, normal weight aggregate (NWA), and lightweight aggregate (LWA). To characterize the relation between various concrete components and the mechanical characteristics of LWAC, extensive studies have been conducted, proposing empirical equations using regression models based on their experimental results. However, these results obtained from laboratory experiments do not provide consistent prediction accuracy due to the complicated relation between materials and mix proportions, and a general prediction model is needed, considering several mix proportions and concrete constituents. This study adopts the artificial neural network (ANN) for modeling the complex and nonlinear relation between constituents and the resulting compressive strength and elastic modulus of LWAC. To construct a database for the ANN model, a vast amount of detailed and extensive data was collected from the literature including various mix proportions, material properties, and mechanical characteristics of concrete. The optimal ANN architecture is determined to enhance prediction accuracy in terms of the numbers of hidden layers and neurons. Using this database and the optimal ANN model, the performance of the ANN-based prediction model is evaluated in terms of the compressive strength and elastic modulus of LWAC. Furthermore, these prediction accuracies are compared to the results of previous ANN-based analyses, as well as those obtained from the commonly used linear and nonlinear regression models.

Keywords: artificial neural network; compressive strength; elastic modulus; lightweight aggregate concrete; prediction model

1. Introduction

Lightweight aggregate concrete (LWAC) represents a type of concrete which has a low unit weight compared to that of normal weight aggregate concrete (NWAC). Because of the low mass density, LWAC has the advantages associated with reduced self-weight of structures and has been applied in long-span bridges and high-rise buildings [1]. Furthermore, structural LWAC, with a strength that is similar to NWAC, enables the reduction of construction cost as it requires less reinforcement, smaller supporting deck members, beams, and piers, and less earthquake damage. Another important economic benefit of LWAC is the transportation cost savings achieved by improving the lifting efficiency in the construction field and lowering shipping cost, compared to conventional NWAC products. The unique advantages of LWAC allow a wide variety of real world applications that are continuously increasing [2].

LWAC consists of the same concrete components as conventional NWAC with a partial or complete replacement of normal weight aggregate (NWA) with lightweight aggregate (LWA). Commercially
available artificial LWAs are generally produced by sintering pyroplastic materials such as slate, shale, clay, and by-products of coal combustion materials at 1200–1300 °C [3]. These LWAs have an inherently great porosity, resulting in low density, low strength, and deformable particles [4,5]. Following ASTM C 330 standard tests [6], these LWAs conform to the specifications of a particle density not exceeding 2000 kg/m³, or a dry loose bulk density less than 1120 kg/m³, 880 kg/m³, and 1040 kg/m³ for fine, coarse, and combined LWA, respectively. LWAC incorporating these LWAs generally has a density lower than 1920 kg/m³ [7]. A lower density of LWAC can be achieved by using a larger amount of porous LWA, resulting in poor mechanical performance. Because the failure of LWAC is influenced by the friable and deformable LWAs, most LWAC has a lower compressive strength and elastic modulus than NWAC.

Extensive efforts have been made to characterize the relation between LWAC constituents and the mechanical properties of compressive strength and elastic modulus. A previous study showed that the compressive strength and elastic modulus of LWAC were inversely proportional to the volume fraction of LWA [8]. The compressive strength of LWAC also depends on not only the content of LWAs, but also their type [9,10]. Hence, these experimental studies indicated that the properties and amount of LWAs influenced the mechanical behavior of LWAC. Furthermore, the mix proportions of LWAC are also essential parameters influencing the performance of LWAC, such as water-to-cement ratio (w/c) and mass of aggregate, water, and binders including cement, fly ash, and silica fume [11]. Considering these factors, some guidelines were provided for estimating the mechanical properties of LWAC, which were not consistently attainable due to the complexities associated with LWA properties and mix proportions [7,12]. Therefore, the reliable prediction model for mechanical characteristics of LWAC is required to extend its use in the construction with ensuring its performance.

To consider the highly complicated relationship between concrete constituents and properties of cement-based construction materials, researchers have employed artificial neural networks (ANN). An ANN is a numerical model using highly interconnected processing of simple computing elements, referred to as neurons, imitating the structure and functions of biological neural systems of the human brain [13]. In the field of construction materials, ANN methods were applied for modeling concrete properties, including mechanical characteristics, fluidity, and durability using concrete components-related information as input parameters [14–16]. Ni and Wang [14] reported that the single-layer ANN model showed a good prediction accuracy for estimating the 28-day compressive strength of NWAC. Note that the ANN models of 11-7-1 from Ni and Wang [14] and 7-5-3-2 from Oztas et al. [16] in Table 1 indicate 11 inputs, seven neurons in one hidden layer, and one output and seven inputs, five and three neurons in each hidden layer, and two outputs, respectively. Douma et al. [15] likewise used a single hidden layer ANN model for the prediction of fluidity and mechanical properties of self-compacting concrete, where results were well-matched to the target value. In the case of LWAC, Alshihri et al. [17] and Tavakkol et al. [18] investigated the ANN-based estimation of compressive strength of LWAC fabricated in the laboratory environment. In addition, the ANN model having a single hidden layer structure was used for predicting the Poisson ratio [19] and compressive strength based on measured ultrasonic pulse velocity [20]. These experimental results provided the feasibility of the ANN to model the nonlinear relation between various parameters and concrete properties. However, as prediction modeling for LWAC has not been fully studied, further research is still desired, to evaluate the optimal ANN architecture and consider extensive data about mix proportions, binders, and aggregates.

This study presents an ANN-based prediction model for mechanical characteristics of LWAC, which enable us to produce high-quality LWAC that satisfies the target performance. First, detailed and extensive data on the mix proportions and the mechanical behavior of LWAC are collected from the literature. The vast amount of data allows to enhance the reliability and accuracy of the prediction model. Input parameters for the ANN model are selected for better modeling of the LWAC, including water-to-binder ratio, amount of binders, density of concrete, and volume fraction of aggregates. Subsequently, the appropriate number of hidden layers and neurons are determined for developing the optimal ANN architectures to obtain high prediction accuracy. Finally, the performance of the
ANN-based prediction model is evaluated and compared to the results obtained from the commonly used statistical models.

2. Research Background

2.1. Artificial Neural Network

An ANN is a network based on a collection of connected neurons used to model the complex relationship between inputs and outputs. As shown in Figure 1, the basic structure of an ANN consists of three types of layers: Input, hidden, and output layers. Depending on the number of hidden layers, ANN is classified into single- or multi-layer perceptron, which has multi-connected neurons. When neurons in the input layer receive an input, the weighted sums of the inputs are transferred to interconnected neurons in the next layer and evaluated using activation functions [13]. The weight and bias values can be determined as the solutions of the optimization problem to minimize the prediction error using the back-propagation algorithm [15].

To optimize the weight and bias, the back-propagation learning is repeated from the output layer back to the input layer in each running step, until there is no further decrease in the mean square error (MSE) of the prediction. After the training is completed with updated weight and bias, new inputs from the test dataset are used in the network to produce the corresponding outputs. The prediction accuracy can be evaluated by the mean absolute percentage error (MAE) and correlation coefficient (R). MSE, MAE, and R are defined as:

\[
MSE = \frac{1}{N} \sum (y_i - y_{di})^2
\]  

\[
MAE = \frac{1}{N} \sum \frac{|y_i - y_{di}|}{|y_i|}
\]

\[
R = \frac{\sum (y_i - \bar{y}_i)(y_{di} - \bar{y}_{di})}{\sqrt{\sum (y_i - \bar{y}_i)^2 \sum (y_{di} - \bar{y}_{di})^2}}
\]

where N is the number of training data, \( y_i \) is the target value, \( y_{di} \) is the predicted result, \( y_j \) is the mean prediction value, and \( \bar{y}_{di} \) is the mean target value. The correlation coefficient is introduced to evaluate the linear dependence between the predicted and target values. Its value ranges from -1 to 1, where 1 indicates the perfect positive correlation and 0 means no linear relation among variables.
2.2. ANN-Based Prediction of Concrete Properties

Previous ANN-based prediction models demonstrated the feasibility for predicting physical and mechanical properties of concrete, as provided in Table 1. The most conventionally used ANN-based prediction mainly focused on the characterization of properties of NWAC, such as the compressive strength, elastic modulus, drying shrinkage, and fluidity [14,22–25]. As these ANN models exhibited acceptable prediction accuracy, their applications were extended to high strength concrete, self-consolidating concrete, recycled aggregate concrete, and LWAC. However, further research on these types of concrete is still needed to enhance the reliability and the prediction accuracy of ANN-based analysis considering various mix proportions and concrete materials. Furthermore, determining optimal numbers of hidden layers and neurons for the ANN model is necessary to model a complex relationship between the inputs and targets. Considering these aspects, this study mainly focuses on the prediction of mechanical properties of LWAC using the ANN model.

Table 1. Previous studies using artificial neural network (ANN) analysis for predicting mechanical behavior of cement-based material.

| Literature                      | Target                                      | ANN Architecture (Number of Neurons in Input-Hidden-Output Layers) |
|---------------------------------|---------------------------------------------|-------------------------------------------------------------------|
| Ni and Wang (2000) [14]         | Compressive strength (65 data)              | 11-7-1                                                            |
| Oztas et al. (2006) [16]        | Compressive strength and fluidity (187 data) | 7-5-3-2                                                          |
| Demir (2008) [22]               | Elastic modulus (159 data)                  | 1-3-1, 1-5-1, 1-3-3-1                                             |
| Alshihri et al. (2009) [17]     | Compressive strength (108 data)             | 8-14-4, 8-14-6-4                                                  |
| Atici (2011) [23]               | Compressive strength (27 data)              | 3-5-1, 4-6-1, 4-6-1                                               |
|                                 |                                             | 3-5-1, 5-6-1, 2-4-1                                               |
| Bal and Buyle-Bodin (2013) [24] | Drying shrinkage (176 data)                 | 11-8-4-1, 11-8-6-1                                               |
|                                 |                                             | 11-9-4-1, 11-9-6-1                                               |
| Khademi et al. (2016) [26]      | Compressive strength (257 data)             | 14-29-1                                                          |
| Douma et al. (2017) [15]        | Fluidity (114 data)                         | 6-17-1                                                           |
| Hossain et al. (2018) [25]      | Compressive and tensile strength (180 data) | 12-8-1, 10-7-1                                                  |

In the application of the ANN model, several issues have been identified with regard to the database, input variables, and ANN architecture. First, many studies used the data obtained in the laboratory environment, resulting in an acceptable prediction error [14,17,18]. However, the applications of these ANN models are limited to the concrete using specific types of materials. To make a more general ANN-based prediction model, this study collects various data of LWAC mixtures with different mix proportions and concrete materials provided in Section 3. The selection of appropriate input parameters is another important factor to consider for obtaining high prediction accuracy. Considering the input variables used in previous studies and the unique material properties of LWAC, the inputs are determined as shown in Section 4.1. Lastly, the investigation for designing optimal ANN architecture for predicting mechanical properties of LWAC is necessary in terms of the numbers of hidden layers and neurons. Previous studies, listed in Table 1, used various ANN models with one- and two-hidden layers with 3–29 hidden neurons. As an example, 11-7-1 in Ni and Wang [14] depicts 11 inputs, seven neurons in one hidden layer, and one output ANN architecture. Because these experimental studies attained a good prediction accuracy, this study conducts the ANN analysis using the ANN model with the range of these hidden layers and neurons, as provided in Section 4.2. Finally, vast data, suitable input variables, and optimal ANN architecture are used for the ANN-based prediction model for LWAC.
3. Establishment of A Database

Accurate and reliable prediction using the ANN model generally depends on the amount and quality of available data. This study conducted a literature review to collect extensive and detailed information on mix proportions, physical properties of composites, and mechanical characteristics of concrete. A total of 149 concrete mixtures (20 NWAC and 129 LWAC) produced with various mix proportion and aggregates were prepared for ANN-based compressive strength analysis [2,4,8,10,27–37]. For the prediction of the static elastic modulus, data from 133 concrete mixtures (20 NWAC and 113 LWAC) were collected [2,4,8,10,27,28,32–37]. The obtained data are summarized in Table 2 listing concrete density (kg/m\(^3\)), water-to-binder ratio (w/b), content of water (kg/m\(^3\)), cement (kg/m\(^3\)), fly ash (kg/m\(^3\)), silica fume (kg/m\(^3\)), coarse NWA (CNWA, kg/m\(^3\)), fine NWA (FNWA, kg/m\(^3\)), coarse LWA (CLWA, kg/m\(^3\)), fine LWA (FLWA, kg/m\(^3\)), volume fraction of aggregate, and the specific gravity of used materials. Detailed information on concrete mixtures is provided in the Appendix A. Note that NWAC is included in the database as control concrete samples without CLWA and FLWA. Compared to the mix proportion of LWAC, the selected data of NWAC have a similar w/b ratio, cement, fly ash, and silica fume content. The variables of mix proportion and volume fraction provided in Table 2 are generally considered as factors influencing the mechanical behavior of concrete [17].

| Mix Proportion and Material Properties | LWAC | NWAC |
|---------------------------------------|------|------|
| Concrete density                      | 1170–2280 kg/m\(^3\) | 2030–2430 kg/m\(^3\) |
| w/b                                   | 0.23–0.55 | 0.25–0.45 |
| Mass                                  |      |      |
| Water                                 | 150–263 kg/m\(^3\) | 158–207 kg/m\(^3\) |
| Cement                                | 300–710 kg/m\(^3\) | 300–640 kg/m\(^3\) |
| Fly ash                               | 0–300 kg/m\(^3\) | 0–300 kg/m\(^3\) |
| Silica fume                           | 0–71 kg/m\(^3\) | 0–96 kg/m\(^3\) |
| CNWA                                  | 0–810 kg/m\(^3\) | 810–1105 kg/m\(^3\) |
| FNWA                                  | 0–1096 kg/m\(^3\) | 288–861 kg/m\(^3\) |
| CLWA                                  | 0–898 kg/m\(^3\) | 0 |
| FLWA                                  | 0–631 kg/m\(^3\) | 0 |
| Volume fraction                       |      |      |
| CNWA                                  | 0–0.31 | 0.30–0.45 |
| FNWA                                  | 0–0.42 | 0.12–0.34 |
| CLWA                                  | 0–0.52 | 0 |
| FLWA                                  | 0–0.39 | 0 |
| Specific gravity                      |      |      |
| Cement                                | 3100–3160 kg/m\(^3\) | |
| Fly ash                               | 2060–2470 kg/m\(^3\) | |
| Silica fume                           | 2000–2280 kg/m\(^3\) | |
| CNWA                                  | 2460–2740 kg/m\(^3\) | |
| FNWA                                  | 2460–2700 kg/m\(^3\) | |
| CLWA                                  | 600–2070 kg/m\(^3\) | |
| FLWA                                  | 1340–1790 kg/m\(^3\) | |

Because several studies used different sizes of specimens for measuring the compressive strength and elastic modulus, the size effect needs to be considered to assure data consistency. The size effect generally presents a reduction of compressive strength and the elastic modulus of concrete with an increasing height-to-width ratio caused by failure of the heterogeneous concrete composite [38]. Therefore, the correction factors are used to convert the data of compressive strength and elastic modulus to equivalent values for the widely used 100 mm by 200 mm cylindrical specimen, referring to the empirical equations from previous studies [38–41]. Here, the correction factors for 28-day compressive strength are 1.051 for \(f_{c,\varnothing100\times200}/f_{c,\varnothing150\times150}\), 0.874 for \(f_{c,\varnothing100\times200}/f_{c,100\times100\times100}\), and 1.230 for \(f_{c,\varnothing100\times200}/f_{c,\varnothing150\times300}\) obtained from \(w/c = 0.49\) high performance lightweight foamed concrete [42]. The correction equation for the static elastic modulus is \(E_{c,\varnothing100\times200} = (E_{c,\varnothing150\times300} − 1.9)/0.9\) obtained...
from normal strength NWAC [41]. Because the investigations of size and shape effect for LWAC were rare, the empirical equations from foamed concrete and normal strength NWAC are used considering the similar failure mechanism induced by the concrete heterogeneity and internal defects of voids. Using these correction factors for the compressive strength and elastic modulus, the database used for the ANN model is updated.

4. Prediction Model for Compressive Strength and Elastic Modulus Using ANN

Because the ANN model has been used for modeling highly nonlinear and complex interactions between input and output variables, the selection of appropriate input parameters and the ANN architecture is critical for reliable and accurate prediction. This section mainly illustrates the selection of input factors and the determination of the optimal ANN architecture for the prediction of mechanical characteristics of LWAC.

4.1. Input Parameters

The selection of appropriate input variables is an important task for enhancing the prediction accuracy of the ANN model, considering the relation between input and target values. Because the strong correlation between mechanical properties of concrete and the amount of constituent materials is generally known, these parameters were adopted as the input for predicting compressive strength and the elastic modulus using ANN models, as summarized in Table 3 [15–17,26]. Commonly used inputs are w/b ratio and mass of water, binders, aggregates, and chemical admixture, which are likewise adopted in this study. However, other parameters such as the sand-to-aggregate ratio, aggregate-to-binder ratio, replacement ratio of binders and aggregates, grade of cement, maximum size of aggregates, and the fine modulus of sand are not included despite their possible relation with mechanical properties, because of the difficulties in data collection, as in [14,43]. Even though previous studies listed in Table 3 provide useful information about the selection of appropriate inputs, NWAC was of primary interest in the prediction. Therefore, additional variables tailored to LWAC are needed to improve the prediction performance.

Table 3. Input variables for the ANN model.

| Input Variables                                                                 | Oztas et al. [16]                                                                 | Alshihri et al. [17]                                                                 | Khademi et al. [26]                                                                 | Douma et al. [15]                                                                 | ANN model |
|--------------------------------------------------------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|----------------------------------------------------------------------------------|-----------|
| w/b ratio, sand-to-aggregate ratio, replacement ratio of fly ash and silica fume, mass of water, chemical admixture | w/c ratio, curing period, mass of FNWA, CLWA, FLWA, silica fume, chemical admixture | w/c ratio, aggregate-to-cement ratio, replacement ratio of recycled aggregate, water-to-total materials ratio, mass of water, cement, CNWA, FNWA, recycled aggregate, chemical admixture | w/b ratio, replacement ratio of fly ash, content of binders, CNWA, FNWA, chemical admixture | w/b ratio, concrete density, mass of water, cement, fly ash, silica fume, volume fraction of CNWA, FNWA, CLWA, FLWA |

Accordingly, this study adopts the density of LWAC and volume fraction of aggregates as the inputs due to the inverse proportional relation to the mechanical performance of LWAC [44]. Because the linear and nonlinear empirical relation between the density of LWAC and compressive strength or elastic modulus has been reported, the use of this value as an input parameter is expected to enhance the prediction accuracy [45,46]. Furthermore, the volume fractions of aggregates are introduced as
an input parameter regarding the amount of LWA in the mixture, replacing the mass. The volume fraction that reflects the actual volume of added LWA can be viewed as another indicator of how much LWA is contained in the mixture in addition to the mass. Thus, the volume fractions are included as the input variables for NWA for comparison.

In summary, the selected input variables used for the ANN model are w/b ratio, concrete density, mass of water, cement, fly ash, silica fume, and volume fraction of CNWA, FNWA, CLWA, and FLWA as provided in Table 3. In the analysis of compressive strength and elastic modulus, these inputs are adopted for the ANN-based prediction.

4.2. Determination of the Optimal ANN Architecture

Determination of the optimal ANN architecture in terms of the number of hidden layers and neurons is the most fundamental part of ANN-based analysis. An excessive number of hidden neurons can cause an over-fit problem due to overestimation in the complex relationship between inputs and targets. An insufficient number of hidden neurons can cause an underfitting problem due to the lack of neurons covering various inputs. Therefore, this study determines the optimal ANN architecture with the minimum MSE value, conducting the tests with consideration to various numbers of hidden layers and neurons. The testing ranges of the numbers of hidden layers and neurons are selected by referring the proposed optimization methodologies and previously applied ANN models. First, many optimized methodologies have been proposed to find appropriate numbers of hidden neurons in the higher-order ANN. Among these methods, three empirical equations are selected to estimate the number of neurons in hidden layers, considering the numbers of inputs and outputs in the ANN models [47–49]. The equations are provided as

\[ N_h = \frac{\sqrt{1 + 8N_i} - 1}{2} \]  

\[ N_h = N_i - 1 \]  

\[ N_h = \frac{4N_i^2 + 3}{N_i^2 - 8} \]  

where \( N_h \) and \( N_i \) are the number of hidden neurons and inputs, respectively. Because a total of 10 input parameters are selected in the previous section, the corresponding numbers of calculated hidden neurons are 4, 9, and 4.4 from Equations (4)–(6), respectively. Furthermore, the architectures of previously applied ANN models (see Table 1) are considered to select the appropriate testing ranges. The applied ANN architectures had a higher number of neurons ranging from 3–29 with one or two hidden layers. Thus, to determine the optimal ANN architecture, this study considers the number of neurons from one to 30, which includes the recommended values from Equations (4)–(6) as well as the used ones in Table 1. In the case of hidden layers in the ANN model, previous studies adopted one- or two-hidden layer ANN models, which showed acceptable prediction accuracy. To evaluate the performance of multi-hidden layer ANN models, this study selects a wide range of hidden layers from 1 to 10.

To determine the optimal ANN architecture with the lowest prediction MSE for testing data, detailed information of the ANN model is provided regarding the backpropagation algorithm, activation function, five-fold cross validation, and used computing resources. This study employs the scaled conjugate gradient backpropagation as a network training scheme that updates weight and bias values according to the scaled conjugate gradient method provided in the MATLAB Deep Learning Toolbox [50]. A nonlinear hyperbolic tangent sigmoid function is employed as an activation function in the hidden layer, and a linear transfer function is used in the output layer. To enhance the reliability of the ANN model, five-fold cross validation is used [51,52]. Once five sets of approximately equal-sized samples are prepared through the random partition process, a subset of each sample is used to fit the ANN model, and the remaining samples evaluate the prediction accuracy of the model. This is
repeated five times. The network error is the average error obtained from the five-fold cross validation method providing greater confidence in the error evaluation. The evaluation of prediction accuracy is conducted using the following computing resources: Intel(R) Core i5-6600 ~3.3 GHz (4 CPUs), NVIDIA GeForce GTX 1080, and 8 GB RAM.

In the determination of the optimal ANN architecture, the averaged $MSE$ obtained is used for reliable ANN-based prediction. To show the convergence of averaged $MSE$ values, the relative $MSE$ defined as $(MSE(1) − MSE(0))/MSE(1)$ is calculated for 50 repetitions, as shown in Figure 2. The results of the relative $MSE$ show a convergence of averaged $MSE$ for multiple repetitions, compared to the result of $MSE(1)$. Due to the high computational cost during the test, the appropriate number of repetitions needs to be selected based on the regression curve from the relative $MSE$ of compressive strength and elastic modulus, marked as “Comp” and “Els” in Figure 2, respectively. The regression curve is $−0.148x^{−3.812} + 0.148$ for compressive strength and $−0.176x^{−3.391} + 0.176$ for the elastic modulus. When the slope of $10^{-4}$ is selected as a threshold of convergence, the minimum numbers of the required repetitions are 7 and 8 for the compressive strength and elastic modulus, respectively, which yield the corresponding $MSE$ values.

![Figure 2. Relative $MSE$ for compressive strength and elastic modulus.](image)

In the prediction of the compressive strength and elastic modulus, the optimal ANN architecture is determined considering $MSE$ values for training and testing and computation time. The $MSE$ results for both training and testing are provided in Figure 3 obtained by the ANN models with the 1–30 neurons and 1–10 hidden layers. As expected, the prediction results for both the compressive strength and elastic modulus show much lower $MSE$ values in training than in testing. When the optimal architecture of the ANN model is determined at the minimum test $MSE$, as provided in Table 4, two hidden layers with 14 neurons in each hidden layer for compressive strength analysis show the best performance with the training and a test $MSE$ of 48.7 and 98.2, respectively. For the elastic modulus analysis, the minimum training and test $MSE$ values are 7.8 and 16.9, respectively, corresponding to four hidden layers and 23 neurons. The training times depicted in Figure 3e,f show that a greater number of hidden layers for given number of neurons increases the computational cost significantly due to more numerical calculation. An overfitting problem at small numbers of hidden neurons and many hidden layers is related to the vanishing gradient problem due to slower optimization in earlier layers than in later layers [53].
5. Evaluation of Prediction Accuracy

Using the input variables and optimal ANN architecture determined in the previous section, the performance of the ANN-based prediction model is evaluated with respect to the compressive strength and elastic modulus of LWAC. Furthermore, the prediction results are compared to those obtained from the linear and nonlinear regression models using the same input data.

5.1. Prediction Results Using the ANN Model

Prediction accuracies for compressive strength and elastic modulus of LWAC are evaluated using the selected inputs and ANN architectures with respect to the square error, $\text{MAE}$, and correlation coefficient. Figure 4 shows the ANN-based prediction results with the square errors of each input data, when the ANN models have two hidden layers and 14 neurons, and four layers and 23 neurons for estimation of the compressive strength and elastic modulus, respectively. For the

**Table 4.** Optimal architecture and prediction accuracy of the ANN model.

| ANN Model | Prediction for Compressive Strength | Prediction for Elastic Modulus |
|-----------|-------------------------------------|---------------------------------|
| Number of layers | 2 | 4 |
| Number of neurons | 14 | 23 |
| Training $\text{MSE}$ | 48.7 | 7.8 |
| Test $\text{MSE}$ | 98.2 | 16.9 |

Figure 3. ANN performance evaluation: (a) training, (c) test, and (e) training time for compressive strength and (b) training, (d) test, and (f) training time for elastic modulus analyses.
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| Compressive strength [MPa] | Square error |
|----------------------------|-------------|
| Target [MPa]               |             |

| Elastic modulus [GPa] | Square error |
|-----------------------|--------------|
| Target [GPa]          |              |

Figure 4. Prediction results from ANN model: (a) compressive strength and (b) elastic modulus.
Table 5. Prediction accuracy of ANN-based models.

| Error Configuration | Compressive Strength | Elastic Modulus |
|---------------------|----------------------|-----------------|
|                     | Training | Test | Training | Test |
| Square error        | $1.3 \times 10^{-3}$ | $-6.2 \times 10^2$ | $3.6 \times 10^{-2}$ | $-2.9 \times 10^2$ | $1.5 \times 10^{-4}$ | $-8.5 \times 10$ | $6.5 \times 10^{-5}$ | $-4.4 \times 10$ |
| MAE                 | 9.6%     | 14.5% | 6.9%     | 8.5% |
| Correlation coefficient | 0.930   | 0.977 |

5.2. Comparative Analysis

In Section 5.1, the prediction performance of the ANN model is validated, and the results are compared to those obtained from the commonly used regression algorithms: The statistical models of linear and nonlinear regression. These regression models have typically been used for modeling the relationship between constituents and concrete properties [18,45,46]. Thus, this study adopts the linear and nonlinear (i.e., second-order polynomial) regression models for the evaluation of prediction performance. Furthermore, their prediction accuracies are compared to those obtained from the ANN models using scale-independent $MAE$.

In the linear regression model, multiple linear regression (MLR) is employed to identify the relationship between two or more independent variables and the dependent variable. The equation for the generally used MLR model is provided as

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_i x_i$$  \hspace{1cm} (7)

where $y$ depicts the properties of LWAC being predicted, $x_i$ depicts the independent variables, $a_0$ is the $y$-intercept, and $a_i$ is the regression coefficient. Using the same input variables and data randomly divided into an 8:2 ratio for training and testing likewise the ANN model, the coefficients are optimized with respect to minimizing the summed square error between predicted and target values. The residuals from MLR model are equally distributed and homoscedastic. Due to the variance of network errors at every analysis, MLR-based predictions are repeated 10 times. The linear regression model with the minimum $MAE$ value for test is provided, as shown in Figure 5. The prediction-accuracy indicators for the compressive strength are 87.3, 16.4%, and 0.841 for the $MSE$, $MAE$, and correlation coefficient, respectively. For the elastic modulus, Figure 5b shows the MLR-based prediction as 12.9, 14.4%, and 0.921 for the $MSE$, $MAE$, and correlation coefficient, respectively. The relatively high prediction errors from MLR-based analysis could be related to the assumption that the relationship between the mixture components and concrete properties is linear.

Considering the complex and nonlinear relationships between the constituents and concrete properties, the nonlinear models employing higher-order polynomials help improve the prediction results. In this study, the multiple nonlinear regression (MNLR) model contains constant, linear, and quadratic terms as follows:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_i x_i + \beta_1 x^2_1 + \beta_2 x^2_2 + \cdots + \beta_i x^2_i$$  \hspace{1cm} (8)

where $\beta_i$ is the coefficient for $x^2_i$. The coefficients of the nonlinear regression model are likewise determined by minimizing the square error between estimated and target values. The same database used in the ANN model is applied for MNLR-based analysis, with an 8:2 ratio for training to testing data quantities. The residuals from MNLR model are also equally distributed and homoscedastic likewise MLR model. The training data optimize the coefficients of the MNLR model, and the prediction performance of this model is evaluated. The prediction results with the minimum prediction error are selected on the basis of the 10 times repetitions, as shown in Figure 6. For the compressive strength prediction, the prediction results are 64.2, 15.0%, and 0.880 for the $MSE$, $MAE$, and correlation
coefficient, respectively. Figure 6b shows the results of the elastic modulus with values of 17.6, 13.4%, and 0.944 for the MSE, MAE, and correlation coefficient. As expected, the quadratic polynomial-based MNLR model demonstrates a better prediction accuracy than the result obtained from the MLR model. Despite the improvement of prediction accuracy using the MNLR model, the ANN-based model shows a better performance.

Figure 5. Prediction results from multiple linear regression (MLR)-based analysis: (a) compressive strength and (b) elastic modulus.

Figure 6. Prediction results from multiple nonlinear regression (MNLR)-based analysis: (a) compressive strength and (b) elastic modulus.
The prediction accuracies obtained from ANN, MLR, and MNLR models are summarized in Table 6 in terms of the scale-independent MAE value. Compared to averaged MLR and MNLR models from 10 times analyses, the ANN-based prediction shows the highest accuracy with MAE of 14.5% and 8.5% for the compressive strength and elastic modulus, respectively. High averaged MAE values from linear and nonlinear regression models among 10 times repetitions show their wide range variations for predicting mechanical properties of LWAC. These variations in prediction accuracies indicate that used statistical models would not provide the reliable prediction results for LWAC. Thus, the ANN-based prediction model is shown to be suitable for characterizing the complex and nonlinear relationship between the concrete component materials and mechanical characteristics of LWAC.

Table 6. Prediction accuracies of ANN, MLR, and MNLR models.

| Prediction Accuracy (MAE) | Compressive Strength | Elastic Modulus |
|--------------------------|----------------------|-----------------|
|                          | Training | Test  | Training | Test  |
| ANN model                | 9.6%     | 14.5% | 6.9%     | 8.5%  |
| Linear regression        | 17.0%    | 19.7% | 19.0%    | 21.4% |
| Nonlinear regression     | 14.3%    | 19.9% | 13.7%    | 20.1% |

6. Conclusions

This study presents the ANN-based prediction model for the compressive strength and elastic modulus of LWAC. The ANN model considers the complex and nonlinear relation between the mechanical properties and the concrete components of binders, NWAs, and LWAs. The database for the ANN model was constructed by collecting experimental data of various mix proportions, material properties, and mechanical properties of LWAC from the literature. Suitable input parameters and the optimal ANN architecture in terms of the number of hidden layers and neurons were determined to obtain a better prediction accuracy. To enhance the reliability of the ANN model, the five-fold cross validation was applied to all training and validation processes. The scaled conjugate gradient back-propagation algorithm was applied to obtain the optimal weight and bias values in the ANN model during the training stage. Subsequently, the prediction accuracy of the ANN model was evaluated. In comparison to previous studies using the ANN-based prediction model for NWAC, the ANN model used in this study showed acceptable prediction accuracy with respect to the compressive strength and elastic modulus of LWAC. Furthermore, a comparative analysis showed that the highest prediction accuracy is obtained by the ANN model compared to the use of statistical linear and nonlinear regression models.

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Conflicts of Interest: The authors declare that they have no conflict of interest.
### Table A1. Data sources.

| Literature                        | Mix Proportion [kg/m³] | Volume Fraction          | Density [kg/m³] | \(\sigma_{28}\) [MPa] | \(E_{28}\) [GPa] |
|-----------------------------------|------------------------|--------------------------|-----------------|-------------------------|-----------------|
|                                   | w/b        | W   | C   | FA  | SF  | CNWA | CLWA | FNWA | FLWA | CNWA | CLWA | FNWA | FLWA |
| Kim et al., 2010. [8]             | 0.38       | 175 | 460 | 0   | 0   | 810  | 0    | 861  | 0    | 0.30 | 0    | 0.34 | 0    | 2300 | 47  | 37.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 608  | 117  | 861  | 0    | 0.22 | 0.07 | 0.34 | 0    | 2280 | 44  | 29.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 405  | 234  | 861  | 0    | 0.15 | 0.15 | 0.34 | 0    | 2220 | 43  | 30.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 203  | 352  | 861  | 0    | 0.07 | 0.22 | 0.34 | 0    | 2200 | 42  | 33.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 0    | 469  | 861  | 0    | 0    | 0.30 | 0.34 | 0    | 2150 | 32  | 30.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 604  | 154  | 861  | 0    | 0.22 | 0.07 | 0.34 | 0    | 2280 | 44  | 31.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 402  | 308  | 861  | 0    | 0.15 | 0.15 | 0.34 | 0    | 2150 | 40  | 26.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 201  | 463  | 861  | 0    | 0.07 | 0.22 | 0.34 | 0    | 2100 | 40  | 24.0 |
|                                   | 0.38       | 175 | 460 | 0   | 0   | 0    | 617  | 861  | 0    | 0    | 0.30 | 0.34 | 0    | 2000 | 37  | 25.0 |
| Bogas and Gomes 2013. [30]        | 0.50       | 225 | 450 | 0   | 0   | 374  | 676  | 0    | 0    | 0    | 0.35 | 0.26 | 0    | 1763 | 35  | -    |
|                                   | 0.50       | 225 | 450 | 0   | 0   | 303  | 676  | 0    | 0    | 0    | 0.35 | 0.26 | 0    | 1686 | 27  | -    |
|                                   | 0.35       | 158 | 450 | 0   | 0   | 374  | 847  | 0    | 0    | 0    | 0.35 | 0.32 | 0    | 1897 | 49  | -    |
|                                   | 0.35       | 158 | 450 | 0   | 0   | 452  | 833  | 0    | 0    | 0    | 0.35 | 0.32 | 0    | 1942 | 66  | -    |
|                                   | 0.35       | 158 | 450 | 0   | 0   | 247  | 846  | 0    | 0    | 0    | 0.35 | 0.32 | 0    | 1776 | 31  | -    |
| Bogas et al., 2015. [31]          | 0.55       | 193 | 350 | 0   | 0   | 382  | 825  | 0    | 0    | 0    | 0.35 | 0.32 | 0    | 1897 | 38  | -    |
|                                   | 0.55       | 193 | 350 | 0   | 0   | 208  | 825  | 0    | 0    | 0    | 0.35 | 0.32 | 0    | 1710 | 19  | -    |
| Nguyen et al., 2014. [4]          | 0.45       | 190 | 426 | 0   | 0   | 445  | 554  | 0    | 0    | 0    | 0.45 | 0.23 | 0    | 1440 | 38  | 19.3 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 445  | 277  | 213  | 0    | 0    | 0.45 | 0.11 | 0.11 | 1380 | 36  | 18.6 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 445  | 0    | 427  | 0    | 0    | 0.45 | 0    | 0.22 | 1320 | 34  | 17.3 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 626  | 554  | 0    | 0    | 0    | 0.45 | 0.23 | 0    | 1490 | 35  | 19.1 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 626  | 277  | 177  | 0    | 0    | 0.45 | 0.11 | 0.11 | 1410 | 33  | 17.0 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 626  | 0    | 354  | 0    | 0    | 0.45 | 0    | 0.22 | 1340 | 31  | 15.3 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 558  | 554  | 0    | 0    | 0    | 0.45 | 0.23 | 0    | 1410 | 31  | 16.3 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 558  | 277  | 189  | 0    | 0    | 0.45 | 0.11 | 0.11 | 1290 | 26  | 13.6 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 558  | 0    | 379  | 0    | 0    | 0.45 | 0    | 0.23 | 1170 | 22  | 11.1 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 673  | 554  | 0    | 0    | 0    | 0.45 | 0.23 | 0    | 1520 | 40  | 18.2 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 673  | 277  | 189  | 0    | 0    | 0.45 | 0.11 | 0.11 | 1400 | 35  | 15.7 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 673  | 0    | 379  | 0    | 0    | 0.45 | 0    | 0.23 | 1280 | 31  | 13.6 |
|                                   | 0.45       | 190 | 426 | 0   | 0   | 1105 | 554  | 0    | 0    | 0.45 | 0    | 0.23 | 0    | 2030 | 52  | 32.7 |
### Table A1. Cont.

| Literatures            | Mix Proportion [kg/m$^3$] | Volume Fraction | Density [kg/m$^3$] | $\sigma_{28}$ [MPa] | $E_{28}$ [GPa] |
|------------------------|---------------------------|-----------------|--------------------|----------------------|----------------|
|                        | w/b | W  | C  | FA | SF | CNWA | CLWA | FNWA | FLWA | CNWA | CLWA | FNWA | FLWA |
| Choi et al., 2006. [33]|    | 0.38 | 175 | 460 | 0 | 0 | 810 | 0 | 861 | 0 | 0.31 | 0 | 0.34 | 0 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 608 | 117 | 861 | 0 | 0.23 | 0.07 | 0.34 | 0 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 405 | 234 | 861 | 0 | 0.16 | 0.15 | 0.34 | 0 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 203 | 352 | 861 | 0 | 0.08 | 0.22 | 0.34 | 0 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 0 | 469 | 861 | 0 | 0 | 0.30 | 0.34 | 0.34 | 0 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 810 | 0 | 645 | 158 | 0.31 | 0 | 0.25 | 0.10 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 810 | 0 | 430 | 316 | 0.31 | 0 | 0.17 | 0.20 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 810 | 0 | 215 | 473 | 0.31 | 0 | 0.08 | 0.29 |
|                        |    | 0.38 | 175 | 460 | 0 | 0 | 0 | 0 | 631 | 0 | 0.30 | 0.34 | 0 | 0.39 |
| Yang and Huang 1998. [34]|    | 0.28 | 178 | 626 | 0 | 0 | 292 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 299 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 311 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 389 | 939 | 0 | 0 | 0.24 | 0.36 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 399 | 939 | 0 | 0 | 0.24 | 0.36 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 415 | 939 | 0 | 0 | 0.24 | 0.36 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 486 | 783 | 0 | 0 | 0.30 | 0.30 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 499 | 783 | 0 | 0 | 0.30 | 0.30 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 519 | 783 | 0 | 0 | 0.30 | 0.30 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 583 | 626 | 0 | 0 | 0.36 | 0.24 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 598 | 626 | 0 | 0 | 0.36 | 0.24 | 0 |
|                        |    | 0.28 | 178 | 626 | 0 | 0 | 0 | 623 | 626 | 0 | 0 | 0.36 | 0.24 | 0 |
| Kockal and Ozturan 2011. [10]|    | 0.26 | 158 | 551 | 0 | 55 | 0 | 592 | 636 | 0 | 0 | 0.37 | 0.24 | 0 |
|                        |    | 0.26 | 157 | 548 | 0 | 55 | 0 | 567 | 633 | 0 | 0 | 0.36 | 0.24 | 0 |
|                        |    | 0.26 | 157 | 549 | 0 | 55 | 0 | 580 | 634 | 0 | 0 | 0.36 | 0.24 | 0 |
| Gesoglu et al., 2007. [36]|    | 0.35 | 192 | 550 | 0 | 0 | 0 | 487 | 862 | 0 | 0 | 0.27 | 0.33 | 0 |
|                        |    | 0.35 | 192 | 547 | 0 | 0 | 0 | 646 | 624 | 0 | 0 | 0.36 | 0.24 | 0 |
|                        |    | 0.35 | 191 | 547 | 0 | 0 | 0 | 465 | 858 | 0 | 0 | 0.27 | 0.33 | 0 |
|                        |    | 0.35 | 193 | 550 | 0 | 0 | 0 | 624 | 628 | 0 | 0 | 0.36 | 0.24 | 0 |
|                        |    | 0.35 | 193 | 550 | 0 | 0 | 0 | 506 | 863 | 0 | 0 | 0.28 | 0.33 | 0 |
|                        |    | 0.55 | 220 | 399 | 0 | 0 | 0 | 509 | 902 | 0 | 0 | 0.29 | 0.35 | 0 |
|                        |    | 0.55 | 220 | 401 | 0 | 0 | 0 | 681 | 658 | 0 | 0 | 0.38 | 0.25 | 0 |
|                        |    | 0.55 | 221 | 403 | 0 | 0 | 0 | 475 | 908 | 0 | 0 | 0.28 | 0.35 | 0 |
|                        |    | 0.55 | 220 | 399 | 0 | 0 | 0 | 631 | 657 | 0 | 0 | 0.37 | 0.25 | 0 |
|                        |    | 0.55 | 218 | 397 | 0 | 0 | 0 | 525 | 895 | 0 | 0 | 0.29 | 0.34 | 0 |
|                        |    | 0.55 | 219 | 399 | 0 | 0 | 0 | 706 | 657 | 0 | 0 | 0.39 | 0.25 | 0 |
### Table A1. Cont.

| Literatures | Mix Proportion [kg/m³] | Volume Fraction | Density [kg/m³] | $\sigma_{28}$ [MPa] | $E_{28}$ [GPa] |
|-------------|------------------------|----------------|----------------|---------------------|----------------|
|             | w/b  | W  | C  | FA | SF | CNWA | CLWA | FNWA | FLWA | CNWA | CLWA | FNWA | FLWA |
| Chi et al., 2003. [32] | 0.28 | 171 | 602 | 0 | 0 | 0 | 297 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2166 | 42 | 22.9 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 396 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2108 | 38 | 21.5 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 495 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 2051 | 35 | 20.1 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 594 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1993 | 32 | 18.7 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 297 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2112 | 33 | 20.3 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 396 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2054 | 30 | 16.5 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 495 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 1997 | 28 | 16.5 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 594 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1939 | 23 | 13.8 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 297 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2072 | 30 | 18.2 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 396 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2014 | 26 | 15.5 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 495 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 1957 | 23 | 14.2 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 594 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1899 | 21 | 13.3 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 304 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2166 | 44 | 22.8 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 406 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2108 | 41 | 21.7 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 507 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 2051 | 39 | 18.9 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 608 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1993 | 36 | 18.2 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 304 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2112 | 37 | 21.4 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 406 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2054 | 33 | 18.2 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 507 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 1997 | 30 | 17.4 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 608 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1939 | 28 | 16.1 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 304 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2072 | 27 | 17.1 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 406 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2014 | 26 | 17.0 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 507 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 1957 | 25 | 15.2 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 608 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1899 | 22 | 14.8 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 317 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2166 | 48 | 23.1 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 422 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2108 | 47 | 21.9 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 528 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 2051 | 46 | 20.9 |
|             | 0.28 | 171 | 602 | 0 | 0 | 0 | 634 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1993 | 43 | 19.8 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 317 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2112 | 38 | 21.9 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 422 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2054 | 38 | 21.4 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 528 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 1997 | 39 | 20.6 |
|             | 0.39 | 202 | 517 | 0 | 0 | 0 | 634 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1939 | 38 | 18.0 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 317 | 1096 | 0 | 0 | 0.18 | 0.42 | 0 | 2072 | 31 | 19.3 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 422 | 939 | 0 | 0 | 0.24 | 0.36 | 0 | 2014 | 30 | 17.9 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 528 | 783 | 0 | 0 | 0.30 | 0.30 | 0 | 1957 | 28 | 16.3 |
|             | 0.50 | 226 | 453 | 0 | 0 | 0 | 634 | 626 | 0 | 0 | 0.36 | 0.24 | 0 | 1899 | 30 | 15.4 |
Table A1. Cont.

| Literatures         | Mix Proportion [kg/m³] | Volume Fraction | Density [kg/m³] | $\sigma_{28}$ [MPa] | $E_{28}$ [GPa] |
|---------------------|------------------------|-----------------|-----------------|--------------------|----------------|
| w/b W C FA SF CNWA CLWA FNWA FLWA | w/b W C FA SF CNWA CLWA FNWA FLWA | w/b W C FA SF CNWA CLWA FNWA FLWA | w/b W C FA SF CNWA CLWA FNWA FLWA | w/b W C FA SF CNWA CLWA FNWA FLWA | w/b W C FA SF CNWA CLWA FNWA FLWA |
| Kayali, 2008. [35]  | 0.27 172 300 300 40 1001 0 288 0 0.37 0 0.12 0 | 2134 56 32.5 | 0.23 150 300 300 40 0 898 0 233 0 0.52 0 0.14 | 1540 45 16.7 | 0.30 193 300 300 40 0 766 0 162 0 0.45 0 0.10 | 1747 63 23.7 |
| Guneyisi et al., 2012. [29] | 0.36 207 370 142 57 894 0 626 0 0.33 0 0.24 0 | 2260 58 32.5 | 0.36 207 370 142 57 0 481 0 476 0 0.28 0 0.28 | 1770 53 19.0 | 0.36 207 370 142 57 820 0 626 0 0.33 0 0.24 0 | 2280 56 31.5 |
| Guneyisi et al., 2012. [29] | 0.36 207 370 142 57 0 440 0 511 0 0.28 0 0.32 0 | 1780 67 25.5 | 0.35 193 550 0 0 0 688 688 0 0 0.36 0.27 0 | 2124 48 - | 0.35 193 468 83 0 0 677 677 0 0 0.35 0.26 0 | 2101 45 - |
| Guneyisi et al., 2012. [29] | 0.35 193 385 165 0 0 665 665 0 0 0.36 0.26 0 | 2078 42 - | 0.35 193 523 0 28 0 684 648 0 0 0.35 0.26 0 | 2117 53 - | 0.35 193 495 0 55 0 680 680 0 0 0.35 0.26 0 | 2090 48 - |
| Guneyisi et al., 2012. [29] | 0.35 193 440 83 28 0 670 670 0 0 0.35 0.26 0 | 2085 48 - | 0.35 193 413 83 55 0 669 668 0 0 0.35 0.26 0 | 2070 43 - | 0.35 193 330 165 55 0 657 657 0 0 0.34 0.25 0 | 2062 43 - |
| Rossignolo et al., 2003. [2] | 0.34 263 710 0 71 0 447 192 0 0 0.34 0.07 0 | 1605 54 15.2 | 0.37 251 613 0 61 0 494 215 0 0 0.38 0.08 0 | 1573 50 13.5 | 0.41 245 544 0 54 0 533 228 0 0 0.41 0.09 0 | 1532 46 12.9 |
| Rossignolo et al., 2003. [2] | 0.45 237 484 0 48 0 560 242 0 0 0.43 0.09 0 | 1482 43 12.3 | 0.49 238 440 0 44 0 585 250.8 0 0 0.45 0.10 0 | 1460 40 12.0 | 0.34 263 710 0 71 0 447 192 0 0 0.34 0.07 0 | 1605 54 15.2 |
| Aslam et al., 2016. [37] | 0.36 173 480 0 0 0 360 890 0 0 0.30 0.33 0 | 1790 36 7.9 | 0.36 173 480 0 0 0 375 890 0 0 0.30 0.33 0 | 1810 37 9.6 | 0.36 173 480 0 0 0 390 890 0 0 0.30 0.33 0 | 1850 42 10.2 |
| Aslam et al., 2016. [37] | 0.36 173 480 0 0 0 405 890 0 0 0.29 0.33 0 | 1840 44 11.7 | 0.36 173 480 0 0 0 421 890 0 0 0.29 0.33 0 | 1860 43 13.0 | 0.36 173 480 0 0 0 436 890 0 0 0.29 0.33 0 | 1910 41 15.0 |
| Alengaram et al., 2011. [27] | 0.30 179 515 27 54 0 542 436 0 0 0.43 0.16 0 | 1677 30 7.1 | 0.32 187 510 25 50 0 535 430 0 0 0.42 0.16 0 | 1743 27 6.5 | 0.35 201 501 24 48 0 525 422 0 0 0.41 0.16 0 | 1643 26 5.5 |
| Alengaram et al., 2011. [27] | 0.35 189 465 25 50 0 392 784 0 0 0.31 0.29 0 | 1869 38 10.9 | 0.35 205 504 27 54 0 424 637 0 0 0.33 0.24 0 | 1810 35 10.0 | 0.35 216 532 28 56 0 448 560 0 0 0.35 0.21 0 | 1787 33 8.6 |
| Alengaram et al., 2011. [27] | 0.35 229 564 30 60 0 475 475 0 0 0.37 0.18 0 | 1759 30 7.9 |
Table A1. Cont.

| Literature | Mix Proportion [kg/m$^3$] | Volume Fraction | Density [kg/m$^3$] | $σ_{28}$ [MPa] | $E_{28}$ [GPa] |
|------------|----------------------------|-----------------|--------------------|----------------|-----------------|
| Wee et al., 1996. [28] | w/b 0.40  W 170  C 425  FA 0  SF 0  CNWA 1083  CLWA 0  FNWA 722  FLWA 0  CNWA 0.42  CLWA 0  FNWA 0.28  FLWA 0 | 2400 63 41.8 |
| Wee et al., 1996. [28] | w/b 0.40  W 170  C 383  FA 0  SF 0  CNWA 1083  CLWA 0  FNWA 722  FLWA 0  CNWA 0.42  CLWA 0  FNWA 0.28  FLWA 0 | 2401 70 43.0 |
| Wee et al., 1996. [28] | w/b 0.40  W 170  C 298  FA 128  SF 0  CNWA 1083  CLWA 0  FNWA 722  FLWA 0  CNWA 0.42  CLWA 0  FNWA 0.28  FLWA 0 | 2401 65 41.5 |
| Wee et al., 1996. [28] | w/b 0.35  W 170  C 437  FA 0  SF 0  CNWA 1046  CLWA 0  FNWA 698  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.27  FLWA 0 | 2394 86 45.0 |
| Wee et al., 1996. [28] | w/b 0.35  W 170  C 389  FA 96  SF 0  CNWA 1046  CLWA 0  FNWA 698  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.27  FLWA 0 | 2399 90 44.4 |
| Wee et al., 1996. [28] | w/b 0.30  W 165  C 550  FA 0  SF 0  CNWA 1045  CLWA 0  FNWA 640  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.25  FLWA 0 | 2400 78 44.3 |
| Wee et al., 1996. [28] | w/b 0.30  W 165  C 495  FA 0  SF 0  CNWA 1045  CLWA 0  FNWA 640  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.25  FLWA 0 | 2401 86 44.3 |
| Wee et al., 1996. [28] | w/b 0.30  W 165  C 385  FA 165  SF 0  CNWA 1045  CLWA 0  FNWA 640  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.25  FLWA 0 | 2400 81 43.9 |
| Wee et al., 1996. [28] | w/b 0.25  W 160  C 640  FA 0  SF 0  CNWA 1043  CLWA 0  FNWA 587  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.23  FLWA 0 | 2430 86 45.6 |
| Wee et al., 1996. [28] | w/b 0.25  W 160  C 608  FA 0  SF 0  CNWA 1043  CLWA 0  FNWA 587  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.23  FLWA 0 | 2430 96 46.6 |
| Wee et al., 1996. [28] | w/b 0.25  W 160  C 576  FA 64  SF 0  CNWA 1043  CLWA 0  FNWA 587  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.23  FLWA 0 | 2430 103 46.7 |
| Wee et al., 1996. [28] | w/b 0.25  W 160  C 544  FA 96  SF 0  CNWA 1043  CLWA 0  FNWA 587  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.23  FLWA 0 | 2430 104 46.3 |
| Wee et al., 1996. [28] | w/b 0.25  W 160  C 448  FA 192  SF 0  CNWA 1043  CLWA 0  FNWA 587  FLWA 0  CNWA 0.40  CLWA 0  FNWA 0.23  FLWA 0 | 2430 93 45.8 |
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