Computers and Concrete, *Vol. 19, No. 5 (2017) 457-465*
DOI: https://doi.org/10.12989/cac.2017.19.5.457

A neural-based predictive model of the compressive strength of waste LCD glass concrete

Chih-Han Kao[1], Chien-Chih Wang[*2] and Her-Yung Wang[3]

[1]*Department of Civil Engineering and Engineering Management, National Quemoy University, 892, Kinmen County, Taiwan, R.O.C*
[2]*Department of Civil Engineering and Geomatics, Cheng Shiu University, 83347, Kaohsiung City, Taiwan, R.O.C*
[3]*Department of Civil Engineering, National Kaohsiung University of Applied Sciences, 80778, Kaohsiung City, Taiwan, R.O.C*

(Received November 21, 2016, Revised January 15, 2017, Accepted January 16, 2017)

Abstract. The Taiwanese liquid crystal display (LCD) industry has traditionally produced a huge amount of waste glass that is placed in landfills. Waste glass recycling can reduce the material costs of concrete and promote sustainable environmental protection activities. Concrete is always utilized as structural material; thus, the concrete compressive strength with a variety of mixtures must be studied using predictive models to achieve more precise results. To create an efficient waste LCD glass concrete (WLGC) design proportion, the related studies utilized a multivariable regression analysis to develop a compressive strength waste LCD glass concrete equation. The mix design proportion for waste LCD glass and the compressive strength relationship is complex and nonlinear. This results in a prediction weakness for the multivariable regression model during the initial growing phase of the compressive strength of waste LCD glass concrete. Thus, the R ratio for the predictive multivariable regression model is 0.96. Neural networks (NN) have a superior ability to handle nonlinear relationships between multiple variables by incorporating supervised learning. This study developed a multivariable prediction model for the determination of waste LCD glass concrete compressive strength by analyzing a series of laboratory test results and utilizing a neural network algorithm that was obtained in a related prior study. The current study also trained the prediction model for the compressive strength of waste LCD glass by calculating the effects of several types of factor combinations, such as the different number of input variables and the relevant filter for input variables. These types of factor combinations have been adjusted to enhance the predictive ability based on the training mechanism of the NN and the characteristics of waste LCD glass concrete. The selection priority of the input variable strategy is that evaluating relevance is better than adding dimensions for the NN prediction of the compressive strength of WLGC. The prediction ability of the model is examined using test results from the same data pool. The R ratio was determined to be approximately 0.996. Using the appropriate input variables from neural networks, the model validation results indicated that the model prediction attains greater accuracy than the multivariable regression model during the initial growing phase of compressive strength. Therefore, the neural-based predictive model for compressive strength promotes the application of waste LCD glass concrete.

Keywords: waste LCD concrete; compressive strength; back propagation neural networks; multivariable regression analysis; input variable strategy

1. Introduction

Waste management is a significant issue today. The methods of waste recycling need to be developed to ensure that the impact on the environment will be reduced. Therefore, a study of green construction methods has been adopted to explore material innovations. Concrete production consumes massive amounts of resources and energy, and this industry is responsible for approximately 5-8% of worldwide greenhouse gas emissions (Scrivener and Kirkpatrick 2008). If traditional concrete materials could be replaced by waste materials, this would not only reduce the pollution of environment but also enhance the performance of concrete and reduce its cost. These advantages will promote its practical application in construction engineering (Chun *et al*. 2007). The construction industry presents an attractive market for recycling waste glass. There have been several related investigations about the use of industry waste for concrete production. For example, the original cement had been replaced by cement of fly ash and slag; concrete aggregates have been replaced by various glasses or liquid crystal display (LCD) glass (Park *et al*. 2004, Wang and Chen 2008, Wang 2009, Wang and Hung 2010, Sarath *et al*. 2015, Kumar *et al*. 2012). The economic output value of the global LCD industry is 91,011.7 million USD in 2014. Moreover, the output value of Taiwanese LCD industry was 18,656.3 million USD in 2014, and the market share of the Taiwanese LCD industry is approximately 20% (Liu 2015). Moreover, the Taiwanese LCD industry has traditionally generated a huge amount of waste glass that is placed in landfills.

The compressive strength mechanism of original concrete is similar to that of concrete containing waste LCD because there are several pozzolanic materials in LCD waste. Additionally, the use of waste LCD can reduce the percentage of air that has to be added to concrete, increasing its compressive strength (Topcu and Canbaz

∗Corresponding author, Associate Professor
E-mail: ccw@gcloud.csu.edu.tw

http://www.techno-press.org/?journal=cac&subpage=8

ISSN: 1598-8198 (Print), 1598-818X (Online)

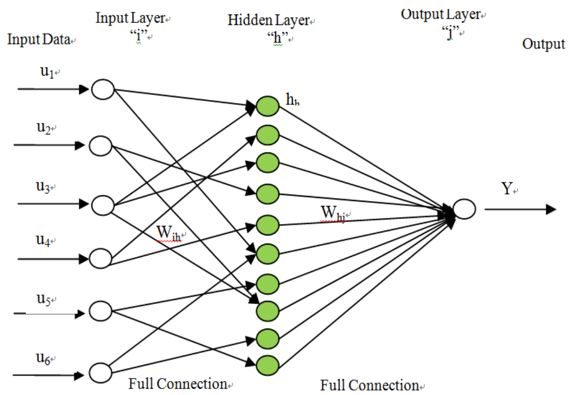

Fig. 1 The network structure of the BPNN

2004, Lin *et al*. 2009). Furthermore, Liang *et al.* (2015) found that the recycled fine glass aggregate contents have significant impact on the workability, compressive strength, the elastic modulus, the peak and the ultimate strains of recycled fine glass aggregate concrete. Wang *et al.* (2014) have adopted the use of waste LCD as the fine aggregate in the production of waste LCD glass concrete (WLGC). In their experiments, all of composed materials such as cement, fly ash, slag, waste glass sand, nature sand, coarse aggregate, the water/cement ratio and curing age were used as the controlling variables for the design of the mix proportions and the compressive strength as the resulting index. They utilized a multi-variable regression analysis to develop the mix design proportion equation for WLGC. However, the relationship between controlling variables and resulting index was nonlinear and had multiple dimensions (Zain *et al.* 2008). Consequently, the predictive accuracy of Wang's equation of mix design proportions for WLGC was 0.96 because it is a first order equation. This equation cannot precisely simulate such a complex relationship. Additionally, the original process of determining the mix proportions of concrete has some difficulty because the proportions of every material must be found by searching a table of factors. This method does not produce the desired strength, the calculations are cumbersome, and there are a number of tables that must be searched prior to arriving at a trial mix proportion. Moreover, there are variations in the attainment of the desired strength and may even be below the target strength and fail (Shanker and Sachan 2014). To ensure the reliability of WLGC, and reduce the unnecessary excess material consumption by developing a more accuracy predictive and numerical model of mix design proportion, this study has developed a numerical model for accurately predicting the compressive strength of WLGC through an appropriate algorithm. Furthermore, to promote the best accuracy of the new non-linear predicting model, this study has researched a suitable pattern for selecting the inputting variables by the characteristics of an algorithm and the material property of WLGC.

2. Analysis of the algorithm

A neural network (NN) simulates the biological learning mechanism to construct a network of computing nodes. The principle feature of this flexible network is a multiple-layer feedforward neural network (MFNN) that can precisely describe complex nonlinear relationships in a realistic manner. The NN method has been well utilized to construct prediction models by using its excellent nonlinear mapping ability (May *et al.* 2011). Peng *et al.* (2010) reported that nonlinear regression analysis provided greater accuracy at early concrete ages and that a back propagation NN (BPNN) was the best choice. In this manner, an NN-based predictive model of concrete mix design proportions can reduce the number of experiments (Ji *et al*. 2006). Through the use of an NN-based model, the cost and resource consumption of concrete experiments can be reduced (Tao *et al.* 2006). Furthermore, Shanker and Sachan (2014) reported that the predictive ability of NN-based model avoids errors in the design of the concrete mix proportion caused by table searches for factors. As a result, the BPNN has been adopted to develop the predictive model of concrete mix design proportions because of its novel performance. Therefore, this study utilized a non-statistical algorithm to accurately map the nonlinear relationships of the WLGC mix design proportions.

The appropriate network development of a BPNN can enhance its predictive performance. The following section describes the learning mechanism of a BPNN and discusses the controlling variables of NN-based predictive models through a survey of related investigations that have allowed the construction of a precise prediction model for WLGC.

2.1 Basic concept of a BPNN

The network structure of a BPNN is composed of multiple layers (input layer, hidden layer and output layer). Each layer has nodes (computing units) that can appropriately transfer information using nonlinear equations. The number of nodes depends on the characteristics of the actual system. The weights, or transforming functions, are fully connected to each node. The values of the weights indicate the degree of the relationship. The appropriate values of weights determine the precise ability of the BPNN for nonlinear mapping.

The learning mode of a BPNN is supervised learning. The definition of an epoch is that all of the training data of the group have been utilized to adjust the weights between nodes. The weight adjustment of the next epoch is computed by difference between estimated output and results of the realistic system. Moreover, until the output difference is less than a preset threshold, the mechanism of adjusting the weights is a cyclic procedure. The threshold value is determined by accepting a certain value of the estimated error. The BPNN adopts the gradient steepest descent method to search for the best combination of NN weights within the error space. This method allows the BPNN to minimize the estimated error of the predictive model. The network structure of the BPNN is presented in Fig. 1.

2.2 The measuring index of the predictive ability for an NN-based model

The NN algorithm has several types of indices for measuring its predictive ability. The coefficient of determination (R-Square, R^2), which also known as the coefficient of multiple correlation, is a commonly used statistic to evaluate the degree of fit of the model. In regression, the R^2 coefficient of determination is a statistical measure of how well the regression line approximates the real data points (Glantz and Slinker 1990). To compare the predictive ability of the multiple regression analysis, the measuring index of comparison shall be the same. Thus, this study utilized the *R* ratio as the measuring index

$$R = \sqrt{1 - \frac{\sum_i (T_i - Y_i)^{\ 2}}{\sum_i (Y_i - \bar{Y})^2}} \tag{1}$$

T_i=the i^{th} target value of output
Y_i=the i^{th} estimated value of output
i=the number of data points
$\bar{Y}$=the average of the estimated output value

An *R* ratio close to 1.0 indicates that we have accounted for almost all the variability with the variables specified in the model.

2.3 Combinations of input variables vs. predictive ability

Selecting a "best subset" of input variables is a critical issue in forecasting. Inclusion of irrelevant variables does not aid in prediction, and it can even reduce the forecasting accuracy (Utans 1995). Furthermore, there are some factors for selecting the input variables for BPNNs that are relevant, with respect to dimensionality, comprehensibility, computational effort and training difficulty, etc. (May *et al.* 2011). The a priori assumption of the functional form of the NN model is based on some physical interpretation of the system. Irrelevant input variables add noise that interrupts the BPNN training process. Training of the BPNN is slower because the relationships between redundant input variables and the error causes are more difficult to map. The training algorithm may expend resources adjusting weights that have no bearing on the output variable, or the noise may mask important input-output relationships (May *et al.* 2011).

Additionally, there is a presumption of non-linearity in the use of BPNNs because important relationships within the data may not be identified by a linear algorithm (May *et al.* 2011). The controlling variables of a system applied successfully within the context of linear regression are not suited to the development of a BPNN. The development of a BPNN needs enough multi-dimensional mathematical space to simulate the complex relationships of the system. Hence, to map a given relationship over the model mathematical space with sufficient confidence, an exponentially increasing number of samples is required (Scott 1992).

2. Controlling variables of an NN for WLGC

To provide a reliable method for searching through the many possible combinations of input variables, the following research was designed to develop a BPNN that determines an optimal, or near optimal set, while working within certain computational constraints. The above mentioned input variable selecting factors will influence the predictive ability of the BPNN. Because the WLGC predicting model developed in this study utilized a BPNN as the algorithm and the material properties of WLGC, the accuracy of its predictive ability was more important than computing efficiency. Thus, the individual relevant controlling variables and their number are discussed in this study. To clarify the effect of each of the two a priori factors, our research evaluated three types of combinations of input variables for the WLGC NN-based model.

The operating mechanism of a BPNN is to develop mapping information from input variables to the output. Thus, the key effect on predictive ability of input variables on the NN is that higher relative influence level of input variable information has a direct relevance to the output. Therefore, the predictive ability of a WLGC NN will be enhanced when the number of relevant input variables is larger than the number of irrelevant input variables. However, the addition of more dimensions to the NN structure can offer enough mathematical capability to enhance the predictive ability of the WLGC model, as noted in section 2.3 that the model simulates the nonlinear relationship between compressive strength and controlling variables. Their number and direct relationships are the two a priori strategies to adjust the NN network structure through the selection of input variables. Furthermore, the evaluation of the number and relevance of input variables depend on the characteristics of the problem (May *et al.* 2011).

This study utilized Wang's accuracy of model prediction (Wang *et al.* 2014) to demonstrate the improvement of NN-based model. The following survey was based on the controlling variables of Wang's model and the evaluation with respect to relevance and number issues for the selection of the controlling variables of the WLGC predicting model. The modified combinations of controlling variables will enhance the predictive performance of the NN-based model.

3.1 Contents of cement and water vs. water/cement ratio

Cement paste joins all the aggregates and is fully incorporated throughout the concrete. The shape and roughness of the surface of the fine aggregate interact with the cement moisture to determine several performance characteristics of the concrete. Hence, it is important to understand the different joining acts between glass sand and original sand at the same water/cement ratio. Furthermore, the water/cement ratio is a key controlling variable of original concrete. Likewise, the water/cement ratio also influences the compressive strength of WLGC.

The water/cement ratio is a first order equation, but the equation of the real relationship between water and cement may be more than first order. For example, the relationship curve of the water/cement ratio and compressive strength was not a straight line in Wang's experiment (2014). Thus, this study has divided the indirect variable of water/cement ratio into two direct variables (amounts of water and cement) as controlling variables of the WLGC NN-based predictive model. The adjusted combination of input variables can be utilized to observe the effect of expanding the input variables.

3.2 Binder ratio of glass sand

The flow ability, elastic ratio, surface roughness, compressive strength and water content of glass sand are different from those of the original sand. Thus, the percentage of contained air and bulk density of WLGC have negative trends with increasing binder-ratio of glass sand. Additionally, the dynamic elastic ratio and the compressive strength of WLGC have positive trends with an increasing glass sand binder-ratio. However, Hussain and Chandak (2015) reported that the compressive strength of WLGC had a maximum value when the binder-ratio of glass sand was 10%. Moreover, the compressive strength of WLGC was higher than that of original concrete when the binder-ratio of glass sand was over 30% (Adaway and Wang 2015). Thus, the present study selected the binder-ratio of glass sand as a controlling variable of the WLGC predictive model.

3.3 Amounts of fine aggregate and coarse aggregate

The main source of the compressive strength of concrete is derived from the aggregate. Because the compressive strength of the aggregate is the highest of all the materials of concrete, increasing the aggregate will increase the compressive strength of concrete. The fine aggregates fill the gaps between the coarse aggregates within the concrete by distributing the pressure to all the aggregates. Thus, the amount of the fine aggregate is dependent upon the quantity of the coarse aggregate. Furthermore, the total amount of fine aggregate and coarse aggregate can be treat as a single input variable of the NN-based model for WLGC. It will be a possible choice to adjust the combination input variable. The number of traditional controlling factors of original concrete has been decreased to focus on the influencing level of the key controlling variables in the NN-based model of WLGC.

3.4 Binder ratio of fly ash and slag

The electrical power industry promotion of fly ash and slag concrete is similar to the situation of WLGC. Thus, Kou and Poon (2009), Hwang (1999) and Lin *et al.* (2012) have researched the effect on compressive strength when fly ash and waste glass were added as alternatives to cement and sand for concrete. The result of their studies indicated that the compressive strength of fly ash concrete had larger strength increments during the initial stage of concrete curing. These results demonstrated that the quantity of fly ash influences the compressive strength of WLGC. The amount of cement-slag can also affect the compressive strength of concrete during the period of water curing (Sajedi *et al.* 2012). Additionally, this study adopted the results of Wang (2014) to validate the NN-based model. To ensure a consistent comparison, the model of this study also adopted the quantities of fly ash and slag as controlling variables.

3.5 Age of curing

WLGC utilizes original cement, slag and fly ash as the adhesive material of aggregates. The hydration of these pozzolanic materials require sufficient time of to achieve maximum hardness. The cement and fly ash induce pozzolanic reactions as the age increases, acting as a binder (Hanehara *et al*. 2001). Thus, the curing age is one of controlling variables for the WLGC NN-based predictive model (Chopra *et al*. 2015).

4. The development of the WLGC NN-based predictive model

The relationships between the combinations of the controlling variables and the compressive strength of WLGC are nonlinear, as has been mentioned previously. To simulate these complex relationships, this study was based on a BPNN to develop a predicting model of the compressive strength of WLGC. Additionally, this study utilized Matlab 12.0 to analyze the data of Wang *et al*. (2014). The following descriptions form the basis of the modeling.

4.1 Selection of input variables

To evaluate the appropriate combinations of input variables, this study developed three types of input variable combinations. The “A” type combination of input variables is a comparison of the baseline, which is an original combination of input variables for the WLGC NN-based model. The belief of dimensionality for the NN structure is implemented for the “B” type combination of input variables. The structure of input-output relevancy is implemented for the “C” type combination of input variables. The details of related descriptions are as follows.
One type had a combination of 7 input variables that were the same as the controlling variables of Wang’s model (2014) (“A” type combination of input variables).

The second type had a combination of 8 input variables that were discussed in section 2.3 (“B” type combination of input variables). This combination divided the variable “water/cement” into two variables: “amount of water” and “amount of cement”. This has been added to the input variables of the “A” type combination for the training of the WLGC NN-based model. Through the comparison of the R ratio values, this study determined the effect of the number of input variables on the training of the BPNN.

The third type had combinations of 6 input variables that were discussed in section 2.3 concerning the relevance of input variables (“C” type combination of input variables). This has reduced the influence of irrelevant input variables contained in the “A” type combination on the training of the WLGC NN-based model. This model combined the two variables “amount of fine aggregate” and “amount of coarse aggregate” into one variable, “total amount of aggregates”, which was based on the “A” type combination of input variables.

4.2 Building the groups of training data and testing data

The number of data sets was 72, which were obtained from Wang (2014). The training data of NN are the imitating objects for weight adjustment of the NN structure. The higher the number of training data in the group is, the more realistic the actual simulation will be for the training. Furthermore, the testing data of NN are the examining objects for the weight adjustment of the NN structure. To enhance the predictive ability, the well training is more important than examining the output of the stage. Furthermore, the comprehensive learning of NN can avoid the computation of false mapping by the full different states of the training data. Thus, the planning of dividing the data follows the customary practice that the proportion of training data to testing data is about 5:1. This study followed the rules of random and full selection and divided the data into groups of training data (60 sets) and testing data (12 sets). The group of training data was utilized to adjust the initial weights of the BPNN, and the group of testing data was adopted to validate the model that was developed in this study.

4.3 Setting the structure of the network

The number of dimensions of the mathematic space was based on the structure of the network. Therefore, through the appropriate setting of the network structure, the model can actually simulate the realistic system. The number of nodes of the input layer was determined by the number of controlling variables of the model. The number of nodes of the output layer of the BPNN was determined using the results of model. The number of nodes of the output layer of the WLGC NN-based predicting model was 1. The number of nodes in the hidden layer of the BPNN was set by the degree of complexity of the realistic system. The accuracy of Wang's predicting model was demonstrated by an *R* ratio of 0.96, demonstrating that the linear regression algorithm can nearly simulate the entire WLGC mechanism. This result demonstrated that the WLGC compressive strength system is not very complex. Consequently, 10 nodes were selected for the hidden layer of the WLGC NN-based predicting model. The network structure of the BPNN that was developed in this study is presented in Fig. 1.

4.4 Setting the learning parameters

There are two important parameters of weight adjustment: one is the learning rate (α), and the other is the moment rate (m). These two parameters control the amount of weight adjustment. The learning process of NN can speedily reach the convergence state for when the values of the two parameters are high, but it is possible to incur a faulty convergence in which the search process of the optimum weight combination will be skipped. Additionally, the accuracy of the analysis of a BPNN can be enhanced by low values of these two parameters. However, this study attaches great importance to the accuracy of the predictive result versus the speed of convergence of a BPNN. Thus, the α value was set at 0.001 and m was at 0.01 for the

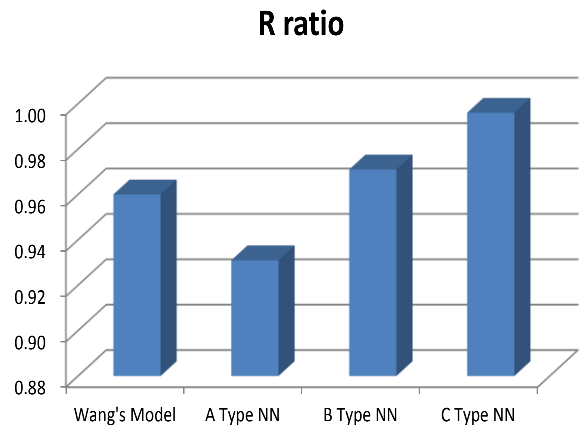

Fig. 2 The comparison of *R* ratio values with different types of predictive models

BPNN in this study.

4.5 Selecting the transferring function

A BPNN can map nonlinear information using the transferring function of a node. The appropriate selection of the transferring function will enhance the correct percentage of the estimated output of a NN-based predicting model. The model of this study adopted the sigmoid function as the transferring function. The sigmoid function is a popular choice for BPNNs.

4.6 Recalling the trained model

This study inputs the values of the controlling variables from the group of validated data when the connected weights of the BPNN have been trained by the above-mention processes. Through the mapping and computing processes of the BPNN, the estimated value can be generated. The data group of this case study also computed the estimated output of the WLGC compressive strength of an individual mix proportion.

5. Validation of the model

This study trains the weights of the NN-based predicting model using Matlab 12.0 and the group of the training data. To validate the superiority of the selected number of input nodes, there were three types of input variable combinations for validation of the selected input dimensions of the NN-based predicting model. There are four types of *R* ratio in the figure of each type of NN: the *R* ratios of training, test, validation, and all. Because the *R* ratios of training, test, and all are computed by networks of uncompleted training, the output results of the networks are mapped inexactly in the training state. Those values of the *R* ratio are in oscillation. The value of the *R* ratio of validation is firm and higher than the values of the other three types of *R* ratio that are computed by fully training network. Thus, the *R* ratio of validation is utilized as the *R* value of comparison. Through the comparison of *R* ratio, this study determined the effect of relevance and number of input variables for the training

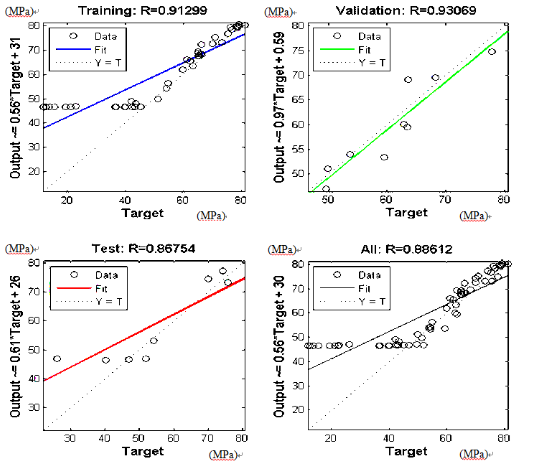

Fig. 3 The *R* ratio of the NN using the “A” type combination of input variables

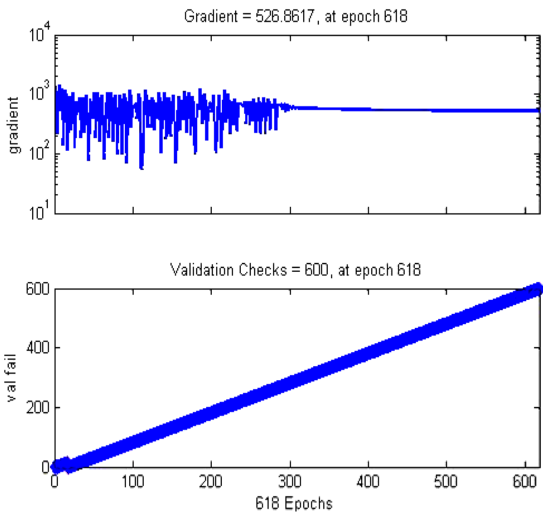

Fig. 4 The gradient curve of the NN using the “A” type combination of input variables

of the BPNN. Moreover, the enhancement of the predictive ability can be demonstrated by the *R* ratio. To clarify the improvement of predictive ability of the modified models, a comparison of the *R* ratios from all the types of predictive models has been presented in Fig. 2.

5.1 A comparison of the predictive ability between “A” and “B” type combinations of input variables

The *R* ratio is an index to measure the predictive ability of an NN-based model. There are values of the training *R*, testing *R*, validation *R* and a total of all *R* ratios. The validation *R* ratio is a measuring index that validates the training of the BPNN. The other *R* ratios are measuring indices for the training process. To validate the superiority of the selected number of the input variables, this study has evaluated the validation *R* ratios from two types input variables. The *R* ratios of the “A” type and “B” type of combinations of input variables can be observed in Fig. 3 and Fig. 5, respectively. This comparison shows that the validation *R* ratio of the “B” type was higher than that of the “A” type.

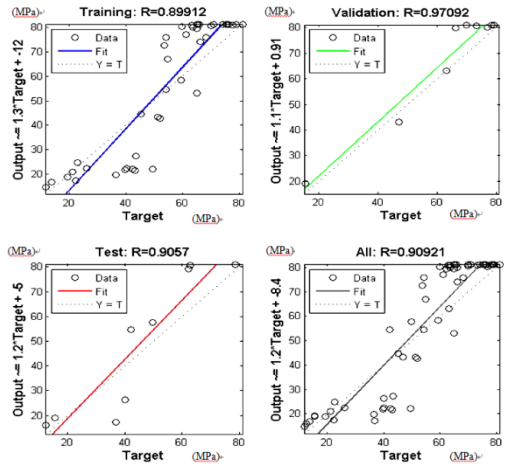

Fig. 5 The *R* ratio of the NN using the “B” type combination of input variables

Furthermore, the learning convergence of the “A” type combination of input variables is demonstrated by the gradient curve shown in Fig. 4. This figure presents an example of the typical training difficulty in which the majority of the weight adjusting actions had occurred prior to the 100th epoch, and the trend of converge occurred during the 100th epoch to 300th epoch, although the error percent could not be reduced. This result can be explained because the number of dimensions was insufficient for the mathematic space of this complex system, causing an early termination of the learning process. The adjusting space of the weights could not satisfy the requirements of the problem using the “A” type combination.

5.2 A comparison of the predictive abilities of the “B” and “C” types of input variables

The number of input variables of the “B” type was larger than that of the “C” type. The *R* ratios of the “B” type and “C” type combinations of input variables are presented in Fig. 5 and Fig. 6, respectively. This comparison shows that the validation *R* ratio of the “C” type was higher than that the “B” type.

Furthermore, the learning convergence of the “C” type combination of input variables is demonstrated by the learning curve shown in Fig. 7. The convergence was finished during the 16th epoch, and the error percent was small. This indicates that the BPNN was easily trained using the appropriate number of input variables. Based on the values of the *R* ratios of validation from the “B” and “C” type combinations of input variables, this study found that the predictive ability of the “C” type combination of input variables was superior to that of the “B” type. The two controlling variables of coarse aggregate and fine aggregate are not the individual controlling variables of the WLGC compressive strength. These two irrelevant variables were combined into one variable, meaning that the influence of an irrelevant variable has been reduced. This demonstrates that the direct relevance of an input variable must be a main part of the input layer, and the input variables should be reduced to enhance the predictive ability of a BPNN.

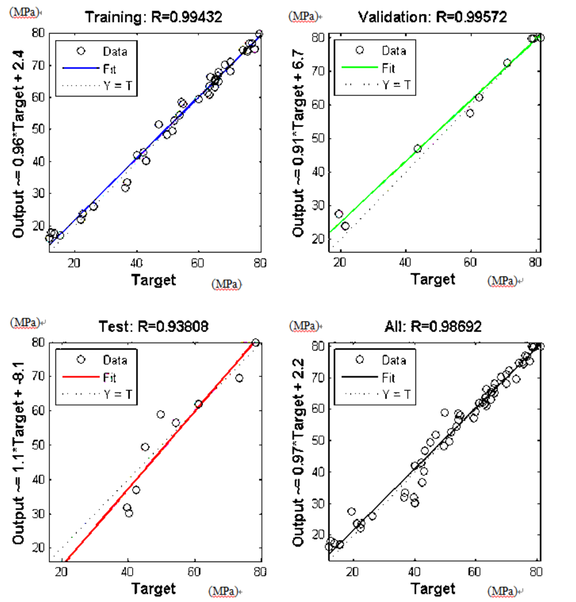

Fig. 6 The *R* ratio of the NN using the "C" type combination of input variables

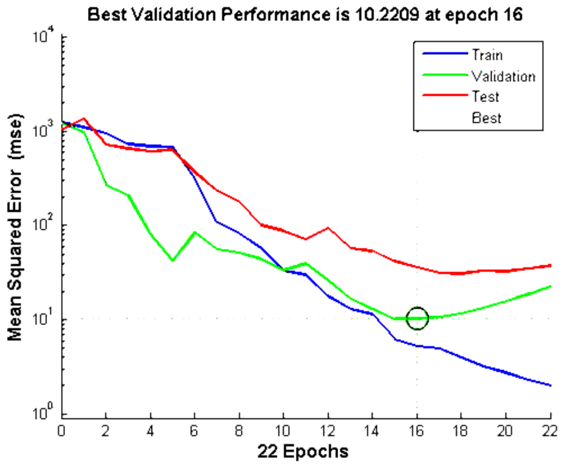

Fig. 7 The learning curve of the NN using the "C" type combination of input variables

Moreover, the comparison indicates that the trend is opposed to discussion (1). This finding indicates that the effect on predictive ability by relevance is stronger than the effect from dimensionality.

5.3 A comparison of the predictive ability of NN-based and multiple regression-based analyses

The highest validation *R* ratio of an NN-based was 0.996. This value is higher than the *R* ratio of Wang's model by approximately 0.036, indicating that the predictive ability of an NN-based model is better than predictive ability of the multiple regression analysis.

Furthermore, this study has compared the experimental compressive strengths with the estimated outputs of the NN-based model and Wang's model, whose data has been randomly utilized in the verification of the NN-base model as presented in Table 1.

Table 1 A comparison of the compressive strengths from two algorithms of the predictive models

No. of Data	Result of the Experiment (MPa)	Predictive Compressive Strength of Wang's Model (MPa)	Predicted Compressive Strength of the NN-based Model (MPa)
1	22.67	11.09	23.62
2	19.44	8.88	27.14
3	46.32	42.28	47.25
4	59.48	59.51	57.43
5	63.61	66.53	62.52
6	79.01	79.99	78.38
7	78.60	72.41	79.60
8	79.30	78.54	79.92
9	81.13	79.26	80.80

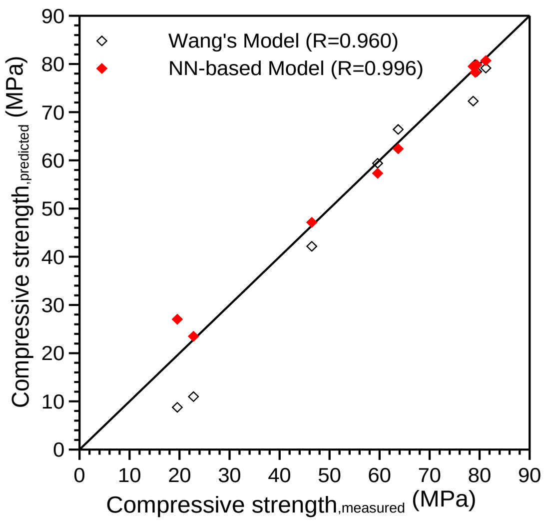

Fig. 8 The comparison of compressive strengths from the algorithms of two predictive models

According the trend of comparison in Table 1, the authors have concluded that the NN-based model has an excellent performance ability that is more able than the multiple regression model to predict the WLGC compressive strength during the initial growing phase. This feature is the main enhancement of the *R* ratio by the NN-based model.

6. Conclusions

According to the evaluation of the accuracy of prediction, this study has enhanced the predictive ability of the model of WLGC compressive strength bases using a BPNN algorithm. Because this new model is based on the assumption of nonlinear behavior, this model has overcome the limitation of multiple regression analysis and has enhanced the predictive ability of the multiple regression model during the initial compressive strength growth phase. The *R* ratio of the multiple regression model was determined to be 0.96, and the *R* ratio of NN-based model was determined to be approximately 0.996. The predicting accuracy of the multiple regression model has been enhanced by the NN-based model, in which the rate of change increased the *R* ratio by 0.036 in this study. This indicates that the NN algorithm is more appropriate for predicting the WLGC compressive strength.

In addition, this study found the appropriate combination of input variables for the characteristics of the NN by the evaluation of the *R* ratio. The selection priority of input variable strategy was that evaluating relevance was more important than adding dimensions for the NN prediction of the WLGC compressive strength. This study has found the key strategy of selecting the input variable for the precise ability of the NN-based predicting model: the model should have a direct relation with the WLGC compressive strength. The discussion in Section 5 suggests the efficient selecting strategy of input variables in which the indirectly-related input variables should be combined as best as possible to reduce the training influence of those variables in the learning process of the NN-based model. The *R* ratio of the original input variable of the NN-based model was determined to be 0.93, and the highest R ratio of the modified input variable of the NN-based model was determined to be approximately 0.996. The predictive accuracy of the original NN-based model has been enhanced by the NN-based model of combined input variables, in that the rate of change in this study increased the *R* ratio by 0.066. This indicates that the relevant input variables of NN have a specific influence on promoting the predictive ability of the NN-based model.

The improved WLGC compressive strength predictive model can reduce the cost and resource consumption of mix proportion experiments, and it can offer highly reliable WLGC.

Moreover, the mix proportion design of WLGC based on the use of the NN-based model is expected to efficiently use cement and aggregate in the production of concrete and numerical model change the design process of the original model that requires table searches. The proposed model can enhance durability, and it has economic and ecological benefits.

Because there are a few strategic issues in the learning mechanism (for example, the transfer function and number of nodes in the hidden layer, etc.) that can enhance the predictive accuracy of the BPNN, those issues concerning the optimization of the structure of the NN are worthy of further investigation to promote the application of WLGC.

References

Adaway, M. and Wang, Y. (2015), "Recycled glass as a partial replacement for fine aggregate in structural concrete-effects on compressive strength", *J. Struct. Eng.*, **14**(1), 116-122.

Chopra, P., Sharma, R.K. and Kumar, M. (2015), "Artificial neural networks for the prediction of compressive strength of concrete", *J. Appl. Sci. Eng.*, **13**(3), 187-204.

Chun, Y.M., Claisse, P., Naik, T.R. and Ganjian, E.S. (2007), "Sustainable construction materials and technologies", *Proceedings of the International Conference on Sustainable Construction Materials and Technology*, Coventry, U.K.

Glantz, S.A. and Slinker, B.K. (1990), *Primer of Applied Regression and Analysis of Variance*, McGraw-Hill, New York, U.S.A.

Hanehara, S., Tomosawa, F., Kobayakawa, M. and Hwang, K. (2001), "Effect of water/powder ratio, mixing ratio of fly ash and curing temperature on pozzolanic reaction of fly ash in cement pastes", *Cement Concrete Res.*, **31**(1), 31-39.

Hussain, M.V. and Chandak, R. (2015), "Strength properties of concrete containing waste glass powder", *J. Eng. Res. Appl.*, **5**(4), 1-4.

Hwang, K., Noguchi, T. and Tomosawa, F. (1999), "Numerical prediction model for compressive strength development of concrete containing fly ash", *J. Struct. Constr. Eng.*, **519**, 1-6.

Ji, T., Lin, T. and Lin, X. (2006), "A concrete mix proportion design algorithm based on artificial neural networks", *Cement Concrete Res.*, **36**(7), 1399-1408.

Kou, S.C. and Poon, C.S. (2009), "Properties of self-compacting concrete prepared with coarse and fine aggregates", *Cement Concrete Compos.*, **31**(9), 622-627.

Kumar, S.C., Varanasi, V.K. and Saha, P. (2012), "Sustainable development using supplementary cementitious materials and recycled aggregate", *J. Mod. Eng. Res.*, **2**(1), 165-171.

Liang, J.F., Yang, Z.P., Yi, P.H. and Wang, J.B. (2015), "Mechanical properties of recycled fine glass aggregate concrete under uniaxial loading", *Comput. Concrete*, **16**(2), 275-285.

Lin, K.L., Huang, W.J., Shie, J.L., Lee, T.C., Wang, K.S. and Lee, C.H. (2009), "The utilization of thin film transistor liquid crystal display waste glass as a pozzolanic material", *J. Hazard. Mater.*, **163**(2), 916-921.

Liu, M.J. (2015), *Flat Panel Display Industry Yearbook*, Industrial Technology Research Institute, Taipei, Taiwan.

May, R., Dandy, G. and Maier, H. (2011), "Review of input variable selection methods for artificial neural networks", *Artif. Neur. Net.-Methodol. Adv. Bio. Appl.*

Park, S.B., Lee, B.C. and Kim, J.H. (2004), "Studies on mechanical properties of concrete containing waste glass aggregate", *Cement Concrete Res.*, **34**(12), 2181-2189.

Peng, C.H., Yeh, I.C. and Lien, L.C. (2010), "Building strength models for high-performance concrete at different ages using genetic operation trees, nonlinear regression, and neural networks", *Eng. Comput.*, **26**(1), 61-73.

Sajedi, F., Razak, H.A., Mahmudb, H.B. and Shafigh, P. (2012), "Relationships between compressive strength cement-slag concrete under air and water curing regimes", *Res. Civil Environ. Eng.*, **1**(4), 202-225.

Sarath, P., Bonda, S., Mohanty, S. and Nayak, S.K. (2015), "Mobile phone waste management and recycling: views and trends", *Waste Manage.*, **46**, 536-545.

Scott, D.W. (1992), *Multivariate Density Estimation: Theory, Practice and Visualization*, John Wiley and Sons, New York, U.S.A.

Scrivener, K.L. and Kirkpatrick, R.J. (2008), "Innovation in use and research on cementitious material", *Cement Concrete Res.*, **38**(2), 128-136.

Shanker, R. and Sachan, A.K. (2014), "Concrete mix design using neural network", *J. Civil Environ. Struct. Constr. Arch. Eng.*, **8**(8), 910-913.

Topçu, İ.B. and Canbaz, M. (2004), "Properties of concrete containing waste glass", *Cement Concrete Res.*, **34**(2), 267-274.

Utans, J., Moody, J., Rehfuss, S. and Siegelmann, H. (1995), "Input variable selection for neural networks: Application to predicting the U.S. business cycle", *Comput. Intell. Fin. Eng. Pro. IEEE/IAFE*, 9-11.

Wang, C.C., Chen, T.T., Wang, H.Y. and Huang, C. (2014), "A predictive model for compressive strength of waste LCD glass concrete by nonlinear-multivariate regression", *Comput. Concrete*, **13**(4), 531-545.

Wang, H.Y. (2009), "A study of the engineering properties of waste LCD glass applied to controlled low strength materials concrete", *Constr. Build. Mater.*, **23**(6), 2127-2131.

Wang, H.Y. and Chen, J.S. (2008), "Study of thin film transition liquid crystal display (TFT-LCD) optical waste glass applied in early-high-strength controlled low strength materials", *Comput. Concrete*, **5**(5), 491-501.

Wang, H.Y. and Huang, W.L. (2010), "A study on the properties of flesh self-consolidating glass concrete (SCGC)", *Constr. Build. Mater*., **24**(4), 619-624.

Zain, M.F.M., Abd, S.M., Sopian, K., Jamil, M. and Che-Ani, A.I. (2008), "Mathematical regression model for the prediction of concrete strength, mathematical methods", *Proceedings of the 10th WSEAS International Conference on Mathematical Methods, Computers in Technology and Intelligent Systems*, 396-402.

CC