Predicting fresh and hardened properties of self-compacting concrete containing fly ash by artificial neural network model

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Abstract. Self-compacting concrete (SCC) is a highly efficient concrete that can be compacted and formed under its own weight without external vibration. However, the constituents of SCC are many and they have diverse material properties. Hence, it is difficult to predict the working performance of SCC with a single factor regression relationship. Therefore, the artificial neural network (ANN) approach is chosen in the present work to simulate the relationship between proportions of constituents and properties of SCC. This paper aims at predicting properties of SCC containing fly ash based on the experimental data available from the literature. The eight input parameters in the proposed models include amounts of cement, water, water to powder ratio, binder, fly ash, coarse aggregate, fine aggregate, and superplasticizers. The four output parameters are V-funnel flow time, slump flow final spread diameter, compressive strength at 28 and 90 days. A procedure to select the number of hidden layer neurons is discussed. Moreover, the parametric analysis of the developed ANN model is conducted to evaluate the effect of input parameters on SCC properties. By comparing the estimated and experimental results, the proposed ANN model shows great potential in predicting the properties of SCC with different percentage volume fractions of fly ash.

1 Introduction

Concrete is the mostly used artificial construction material in the world. However, normal vibrated concrete (NVC) has many limitations on meeting the environmental and economic requirements. In recent years, self-compacting concrete (SCC) has become popular due to its high performance of fresh and hardened properties. To overcome the disadvantages of NVC and to offset the shortage of skilled labour in Japan, SCC was first proposed by Okamura [1]. At a lower level of water to binder ratio, SCC is designed by mixing admixtures to reach required plastic viscosity and high ability of segregation resistance and workability.

To conduct more sustainable production of SCC, the incorporation of mineral admixtures obtained from industrial by-products as the replacement of cement and fine aggregates has been investigated by many researchers. Fly ash is a waste material produced by coal electricity power plants, which is considered to be harmful to soil [2]. The results from the study of Mohammed et al. [3] showed that the addition of fly ash has more significant influence on SCC properties as compared to slag addition. This is because fly ash with the spherical shape increased the flowability [4]. Matos et al. [5] reported that the replacement of fly ash improved the flowability of SCC and then reduced the superplasticizers content. Otherwise, the compressive strength decreased with the increasing amount of fly ash and gained significantly up to 180 days. Although many researchers have studied the properties of SCC with fly ash, most of them draw the conclusion based on the proportioning strategy and experimental validation.

With the development of computer science, different modelling methodologies based on the AI technique have been introduced to the traditional concrete industry. As one of the AI-based models, artificial neural network (ANN) is widely employed to predict SCC properties [6-10]. ANN is composed of large number of interconnected artificial neurons, which can be used to simulate the structure and function of the brain nervous system. Compared to statistical methods, ANN has stronger adaptive ability, learning ability, fault tolerance ability and robustness. Many pieces of research were carried out on predicting mechanical properties of SCC by using ANN. In the study of Asteris et al. [7], the feedforward neural network model showed great potential in predicting the 28 days strength of SCC, where the predicted results correlated well with experimental findings in the literature. Prakash et al. [10] compared the performance of ANN and random kitchen sink (RKS) algorithm on modelling SCC tensile strength. Although these two networks showed high accuracy in the prediction, RKS worked better for large datasets. However, there is insufficient literature on predicting both fresh and hardened properties of SCC incorporating fly ash.

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The aim of this study is to provide a fully trained effective ANN model for predicting main properties of SCC mixes containing fly ash based on proportions. After briefly introducing ANN models and back-propagation network, parameters are described, and databases were normalized. Then, the proposed ANN model was trained and validated to assess the performance by mean square errors and correlation coefficients. Finally, a parametric analysis on the effect of fly ash content and water to binder ratio on SCC properties was carried out.

2 Artificial neural network (ANN)

2.1 ANN model

The artificial neural network is an AI-based method that aims to realize specific functions by imitating the biological neural structures of human being. Essentially, it is the mathematical model to reason about complex logical relationships and process information efficiently. The fundamental processing unit of ANN is the artificial neuron, which is constructed through the preliminary understanding of the human brain system. Each neuron can receive the signal from connected neurons with various weights, which reflect the strength of influence between neurons. An ANN map contains two or more layers, including one input layer, one output layer, and any number of hidden layers. The input and output neurons are determined by proposed problems. However, the number of hidden layers and their nodes are selected by optimum results of repeated trials. Furthermore, the performance of ANN models is significantly influenced by activation functions between layers, such as linear, sigmoid, hyperbolic tangent and piecewise functions.

As a multi-layer feedforward network, back-propagation (BP) is the most commonly used learning algorithm of ANN. Figure 1 shows the typical structure of a BP network with the input layer (M neurons), output layer (N neurons) and one hidden layer (L neurons). In the network, $x_1, \cdots, x_i, \cdots, x_M$ are actual input data, $y_1, \cdots, y_i, \cdots, y_N$ are actual output data, and t_j $(j = 1,2,\cdots,N)$ represents the target output value. The output error is expressed by $e_j = t_j - y_j$ $(j = 1,2,\cdots,N)$ and then back-propagated to the input layer for the weight adjustment of the network. Mean square error (MSE) is employed to determine the network performance using Equation 1.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(actual(t) - predict(t))^2 \qquad (1)$$

2.2 Data collection and parameters

To develop an accurate and well-performed ANN structure, complicated sources of datasets are needed for training, testing and validation phases. A total number of 242 groups of data were gathered from 31 published papers [11-41]. Different evaluation

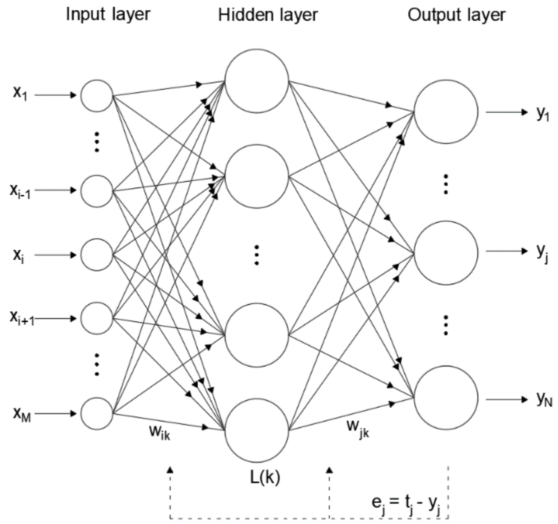

Fig. 1. The architecture of an ANN model

indicators often have different dimensions and units, which will affect the results of data analysis. In order to eliminate the dimensional influence between indicators, Min-max normalization of data is required in the preparation stage.

In this article, the components of SCC mixes containing fly ash, including cement, water, water to binder ratio (W/B), fly ash, binder, fine aggregate (FA), coarse aggregate (CA) and superplasticizers (SP), were selected as input variables. It has been demonstrated that all of these parameters have significant influence on the workability and hardened properties of SCC with fly ash. Four output variables predicted from the network cover the V-funnel time, the slump flow final spread diameter, and the compressive strength at 28 and 90 days of SCC containing fly ash. For the workability of SCC mixes, V-funnel time and slump flow final spread diameter can be recoded as the measure of filling ability and flowability. The statistical information of input and output parameters are shown in Table 1.

Table 1. Input and output parameters

Components	Minimum	Maximum	Average
Input variables (kg/m^3)			
Cement	0.00	670.00	356.76
Water	138.00	331.50	189.34
W/B	0.21	1.00	0.38
Fly ash	0.00	439.00	139.70
Binder	180.00	686.00	510.50
FA	0.00	1180.00	676.97
CA	0.00	1085.20	681.37
SP	0.00	21.84	6.19
Output variables			
V-funnel time (s)	1.31	34.00	8.21
Slump flow (mm)	70.00	910.00	678.09
28 days (MPa)	6.00	88.00	42.34
90 days (MPa)	10.00	92.00	44.30

2.3 BP network modelling

The use of multi-layer neural network technology can realize the nonlinear mapping from the input layer to the output layer, so as to realize the nonlinear prediction of the constituents and properties of SCC mixes. The steps of training the BP network are summarized in Figure 2. To conduct an ANN model with good applicability, a MATLAB program was developed using the neural network toolbox (R2021a). The input databases were divided randomly into three groups, including 70% for training, 15% for validating and 15% for testing. Levenberg-Marquardt was chosen as the training algorithm. All training parameters for this model are summarized in Table 2.

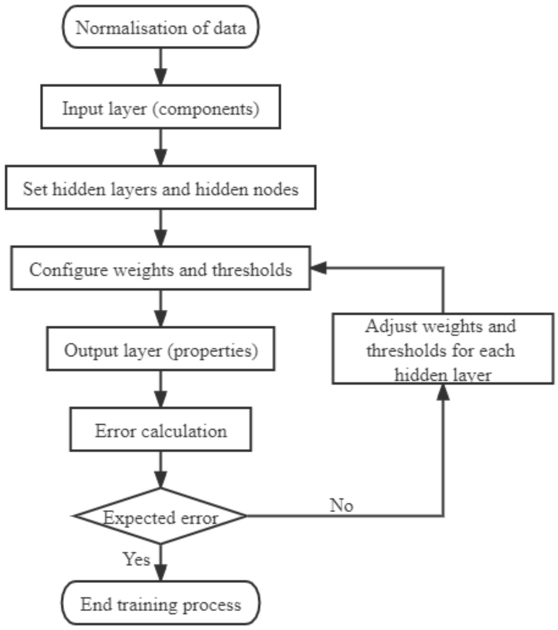

Fig. 2. BP neural network training process

Table 2. Information of the ANN structure

Parameters	
Number of input variables	8
Number of the hidden layer	1
Number of neurons in the hidden layer	10-17 (17)
Number of output variables	4
Training function	Levenberg-Marquardt
Transfer functions	Sigmoid for hidden layer Linear for output neurons
Performance function	Mean Squared Error
Training epoch	20 iterations
Training error	10^{-6}

Different from the number of nodes in input and output layers, the size of the hidden layer is mainly decided by the BP network structure and quality of the training pattern [42]. Here, the ANN network with one hidden layer and 10-17 neurons was considered. The most appropriate number of nodes in the hidden layer relies on the model performance, which was evaluated by MSEs and R values, as shown in Figure 3. The regression values R measured the correlation between output and target numbers. The values close to one mean a stronger connection. Accordingly, the network with structure 8-17-4-1 (presents the number of nodes in each layer) performed best, which was chosen for the following training process. It can be seen from Figure 4, output values predicted by ANN showed a significant correlation with experimental data and the network provided a high estimation accuracy.

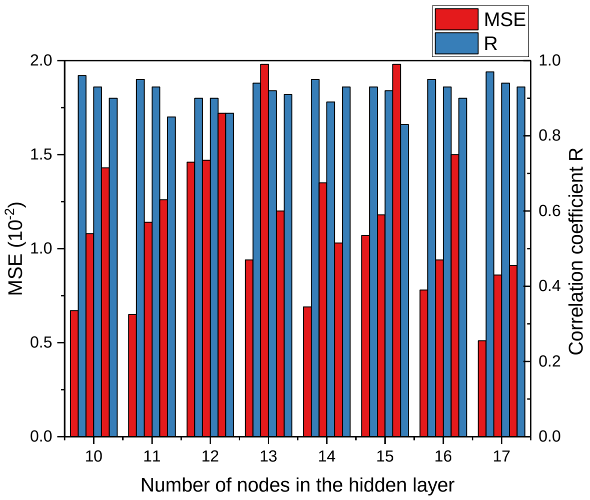

Fig. 3. Performance of the BP network with different sizes of the hidden layer

2.4 BP network validation

The validity and accuracy of a well-trained ANN model are influenced by many factors, such as databases and network parameters. Thus, to evaluate the neural networks and to circumvent potential problems, it is necessary to validate the BP neural network by introducing more unknown data in the range of input parameters used in the training part. The validation dataset contains 21 groups of SCC mixes collected from different experimental resources available in literature [5, 43, 44]. The difference between the predicted results from the existing ANN model and actual validation data is summarised in Table 3. The mean absolute percentage error (MAPE) was employed to evaluate the accuracy of the model, as shown in Equation 2.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{actual(t)-predict(t)}{actual(t)}\right| \times 100\% \quad (2)$$

In Table 3, values of MAPE for predicting V-funnel time, slump flow final spread diameter and compressive strength at 28 and 90 days are 16.9%, 1.9%, 6.6% and 6.5%, respectively. The error in V-funnel time is because a high volume of aggregates and high viscosity mixture can easily stick to the surface of the funnel, which will affect the flowing time. It has been indicated that the proposed ANN model can accurately predict these properties of SCC mixes with fly ash.

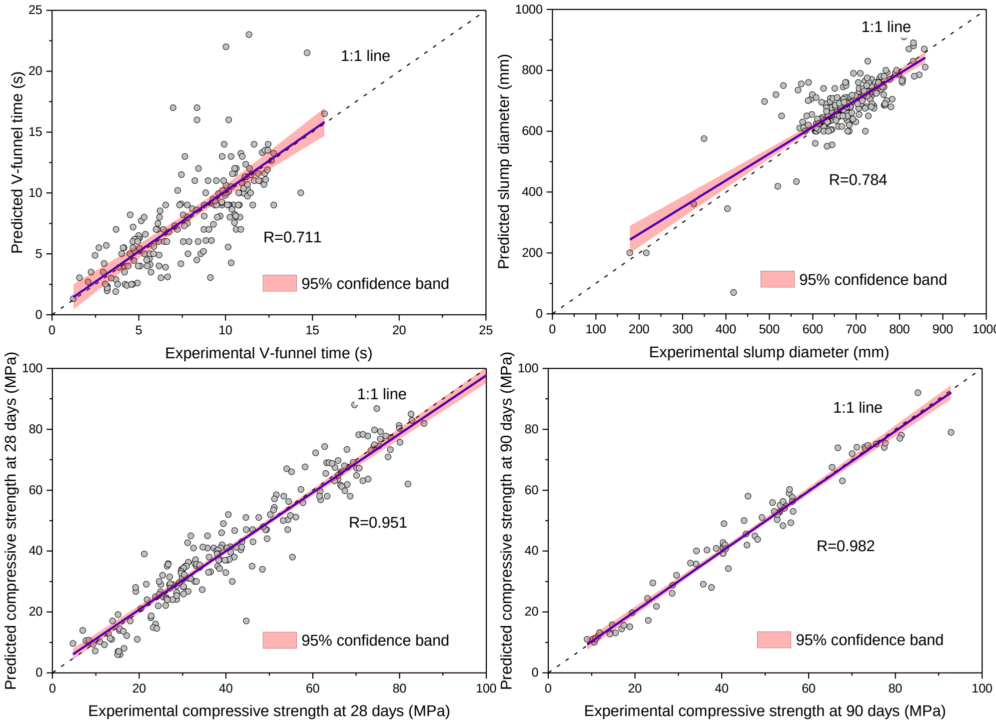

Fig. 4. Correlation between the experimental and predicted values of output parameters

Table 3. The comparison of actual and predicted parameters of validation databases

Author	Year	V-funnel time (s)			Slump flow (mm)			Compressive strength (MPa)					
								28 days			90 days		
		Exp.	ANN	e (%)	Exp.	ANN	e (%)	Exp.	ANN	e (%)	Exp.	ANN	e (%)
Matos et al. [5]	2019	14.0	11.5	17.8	685	683	0.3	54.0	54.1	0.2	64.0	66.4	3.7
		9.0	12.3	36.4	700	683	2.4	57.0	56.5	0.9	70.0	68.2	2.6
		10.0	12.4	24.1	698	679	2.8	63.0	58.8	6.7	75.0	67.9	9.5
		9.0	10.3	14.2	715	688	3.7	46.0	49.2	6.9	58.0	58.5	0.8
		12.0	11.7	2.7	680	686	0.9	57.0	54.2	4.8	60.0	64.4	7.4
		13.0	12.9	0.6	675	687	1.8	59.0	57.4	2.8	74.0	68.6	7.4
		9.0	8.1	10.2	695	706	1.5	35.0	36.7	5.0	46.0	43.0	6.6
		8.0	10.0	24.5	710	700	1.4	39.0	44.4	13.9	54.0	55.5	2.7
		14.0	11.9	15.2	695	698	0.4	43.0	51.0	18.5	63.0	65.2	3.6
Anjos et al. [43]	2020	4.6	5.8	26.3	625	650	4.1	60.1	54.1	10.0	63.0	58.1	7.8
		4.8	5.7	18.9	700	704	0.6	27.8	25.1	9.7	37.5	41.1	9.7
		12.0	11.2	6.6	700	706	0.8	40.9	39.1	4.4	58.3	51.0	12.6
		13.9	6.0	56.7	670	692	3.3	32.6	30.5	6.5	38.3	41.0	7.1
		12.8	12.2	4.5	700	704	0.6	40.0	39.3	1.7	46.5	50.2	8.0
		5.9	5.1	12.4	750	750	0.0	20.0	22.0	10.1	32.1	31.9	0.7
		6.1	6.1	0.6	745	740	0.6	28.4	25.2	11.2	40.7	37.6	7.5
		9.1	5.9	35.6	740	756	2.1	23.0	25.3	10.1	28.0	23.3	16.8
		10.4	6.6	36.2	665	741	11.4	27.5	28.7	4.5	33.5	30.1	10.3
Choudhary et al. [44]	2020	7.0	6.6	5.4	725	724	0.2	55.6	57.0	2.5	60.0	59.0	1.6
		6.9	7.3	5.6	735	730	0.7	54.0	53.2	1.5	59.0	60.2	2.1
		7.3	7.3	0.3	740	738	0.2	45.0	47.9	6.3	56.0	60.3	7.7
MAPE (%)				16.9			1.9			6.6			6.5

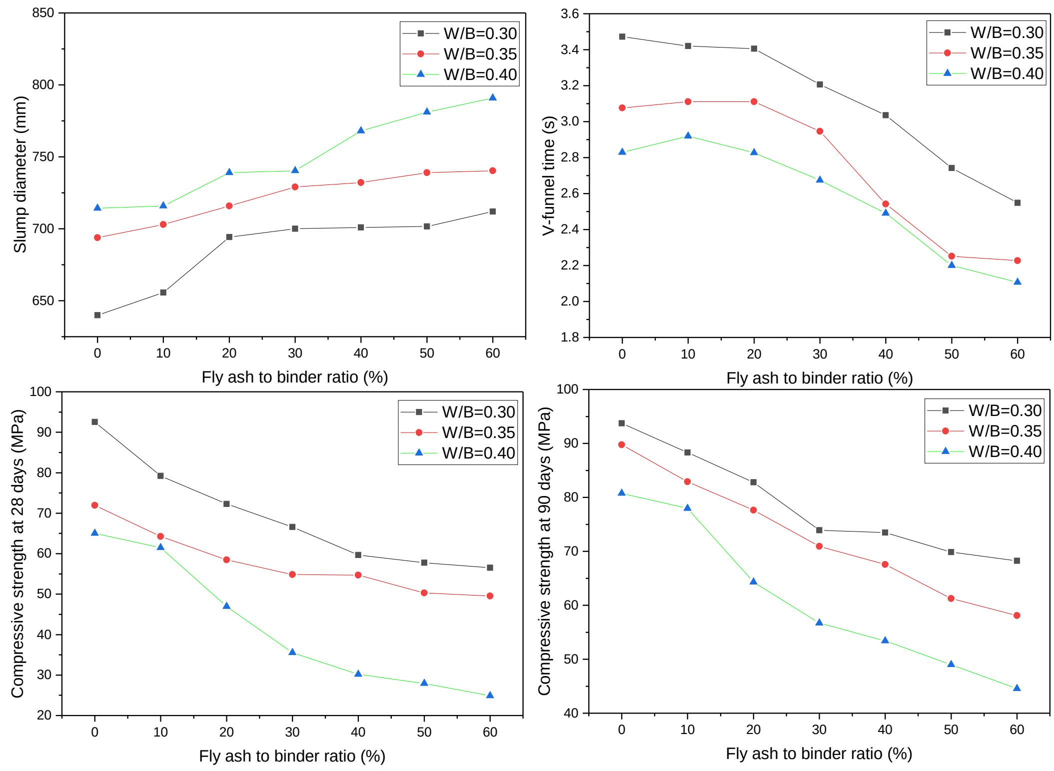

Fig. 5. SCC mixes properties vs different content of W/B ratio and fly ash content

3. Effect of fly ash content and water to binder ratio on SCC properties

It is known that the effect of mineral admixtures on fresh and hardened properties of SCC is nonlinear with uncertainty, which is difficult to describe by statistical analysis. This section gives a reliable parametric assessment to evaluate influence by predicting SCC properties based on the proposed ANN model. In this analysis, input variables related to the fly ash content and W/B ratio were independent, whereas others were set as constant. The sensitivity of SCC properties predicted by the ANN model to changes in fly ash and W/B ratio was evaluated in Figure 5. The results showed that all SCC mixes meet the requirements according to EFNARC [45].

As seen in Figure 5, slump flow final spread diameters increase with increasing fly ash content from 10% to 60% for all mixes. The increase of flowability of SCC containing fly ash was reported by many researchers [4, 39, 46]. The adverse trend can be found in V-funnel times, which can be explained by the spherical-shaped and fine particles of fly ash resulting in improvement of workability. Any substitution level of fly ash reduces compressive strength both at 28 days and 90 days with the constant W/B ratio. Equivalent findings have been reported in published papers [3, 44]. Compared to the hydration of pure cement in SCC mixes without fly ash, a slower pozzolanic reaction takes place between fly ash and $Ca(OH)_2$ in hydrated cement. The increased replacement level of fly ash reduces the amount of cement, resulting in a lower $Ca(OH)_2$ content and a decrease in compressive strength [47]. At a given fly ash content, fresh properties of SCC mixes increase with the increase of the W/B ratio. However, values of compressive strength reduce as the W/B ratio increases from 0.3 to 0.4. The compressive strength of SCC mixes with a W/B ratio of 0.4 decreases more with increasing fly ash content up to 60%.

4. Conclusions

This research discussed the performance of an artificial neural network on predicting fresh and hardened properties of SCC mixes containing fly ash. The back-propagation network was trained based on the Levenberg-Marquardt algorithm. Moreover, the accuracy of the model with the different number of nodes in the hidden layer was investigated and ANN with 17 neurons was chosen for the training and validation process. Based on results of this study, the following conclusions can be drawn:

1. The predicted results of three groups in the modelling part comply well with databases of experimental results.
2. The fully trained ANN model has great potential in predicting properties of SCC, such as the V-funnel time, the slump flow final spread diameter, and the compressive strength at 28 days and 90 days. Mean absolute percentage errors for each variable are 16.9%, 1.9%, 6.6% and 6.5% respectively.
3. The proposed ANN model contributes towards analysing the effect of fly ash content and water to binder ratio on the sensitivity of SCC properties.

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