Compressive Strength Prediction of SCC using ANN

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Abstract

Many environmental and technical advantages have resulted from the use of optimum content of supplementary cementing materials (SCMs) such as limestone filler (LF), fly ash (FA), and silica flume (SF) in Portland cement blends, including improved physical properties, increased concrete industry sustainability, and reduced co_2 emissions. In civil engineering, artificial neural networks (ANNs) have been used to solve a variety of problems, such as predicting the compressive strength of self-compacting concrete The effects and benefits of limestone filler (LF), fly ash (FA), and silica flume (SF) on hardened properties of self-compacting concrete, such as compressive strength, were clearly established, correlating with previous research findings. The results indicated that the developed ANNs model was really a feasible and efficient tool for simulating the compressive strength prediction of LF, FA, and SF self-compacting concrete.

Keywords: Self compacting concrete (SCC), limestone filler, fly ash (FA), silica flume, compressive strength (CS), prediction, artificial neural networks (ANN)

1. INTRODUCTION

Prof. Hajjim Okamura developed self-compacting concrete three decades earlier in Japan [1] . SCC is a highly flowable concrete that can fill forms without the usage of mechanical vibration. It's a self-consolidating, non-segregating concrete that's deposited down by gravity. Self-compacting concrete (SCC) is important since it maintains all the concrete's durability and properties while achieving performance standards. As a result, SCC is capable of self-consolidation without the use of external or internal vibrators. Therefore, bleeding and segregation are avoided while maintaining stability. According to, changing the production process and aggregate type due to variations in mineral additives or cement can have a significant impact on the characteristics of fresh SCC, therefore having a robust combination with minimal influence from external sources is crucial. Scholars are taking priority the use of powder industries by products and waste as mineral additives in this direction because of the environmental benefits. Fly Ash (FA), Silica fume(SF), limestone filler(LF) and a new generation of super plasticizers (SP) have all been proposed to be incorporated into the mix . The type of admixture used is determined by the properties of the concrete. In past few years, silica, fly ash, lime powder, and have been the most commonly used admixtures in civil engineering research.
SCM's can be used in Portland cement replacement for these reasons: (1) their cost is significantly lower than that of Portland cement; (2) some of SCM's increases the early-age

mechanical properties and reduces the aggressive environmental impacts of concrete; (3) improve the long-term performances of concrete.

Artificial Neural Networks (ANNs) are soft computing techniques that are designed to emulate the human neural system in learning from training patterns or data. They are capable to solve extremely complex problems, such as highly non-linear problems, using interconnected computing elements to approximate the non-linear input-output relationship for a variety of applications. The technique of neural networks is increasingly used in the field of civil engineering to predict or optimize more or less complicated phenomena, such as the efficiency factor of slag concretes and fly ash concrete, the concrete mix design incorporating natural pozzolans, properties of self-compacting concrete (SCC) containing fly ash, carbonation depth of fly ash concrete. Some have optimized the compressive strength (CS) of concrete containing cement additions silica fume with self-compacting and high-performance concrete with high volume fly ash. The purpose of this study is to create an easy-to-use ANNs model for predicting the mechanical properties (compressive strength) of concrete containing limestone filler, silica flume, and fly ash. The ANN model was trained on a set of experimental data that included input parameters i.e. binder content (B), limestone filler (LF), fine aggregate (FA), coarse aggregate (CA), fly ash (FA), silica flume (SF), water/binder ratio (W/B), and superplasticiser (SP) and compressive strength (CS) obtained in experiments was take as output parameter. In addition, for evaluating the performance of the developed ANNs model, the analysis is done based on parameters and a comparison were conducted between the experimental and predicted results.

2. METHODOLOGY

ANNs is a soft computing technique, which works on the principle of neural networks inspired by biological nervous systems of living organisms. It can learn by examples of data, such as each the intelligence models. Typically, the architecture of ANNs is composed by a set of interconnected many simple computational nodes operating in parallel so-called the neurons, that are usually arranged into groups systematically, for forming layers in network, which provide a response so-called output from a series of inputs. Thus, the neural networks might be single layer or multilayer, which is consisted by an input layer which have no computation activities, while it was distributing the information from the environment to one or more hidden layers of network, which process the information to provide into the desired output. The number of neurons in the input and the output layers is equal to the variable in the model and the hidden and output layers make the activation function except for input layers. For that, all processing of information in the neural network is happening in the hidden and output layers. The connection strength between the layers is represented by links channels carrying numeric values so-called weights, which are initially set to a random value and adjustable during the training process. The use of nonlinear activation functions in hidden layers improve the ability of ANNs to learn nonlinear relationships between sets of inputs and outputs data; as shown in Figure 1.

The modelling with ANNs required five main stages:

(a) Acquisition and analysis the data, (b) determining the architecture of model, (c) learning process determination, (d) training of the networks and (e) testing and validation of the model proposed for generalization evaluation.

Therefore, Inputs, weights, sum function, activation function, and outputs are the five fundamental components of an artificial neuron. The weighted sums of the input component $(net)_j$ are found by using Eq. (1) as follow:

$$(net)_j = \sum w_{ij} x_i + b \quad (1)$$

Where x_i is the input data; w_{ij} is the weight of the neural model; b is the bias.

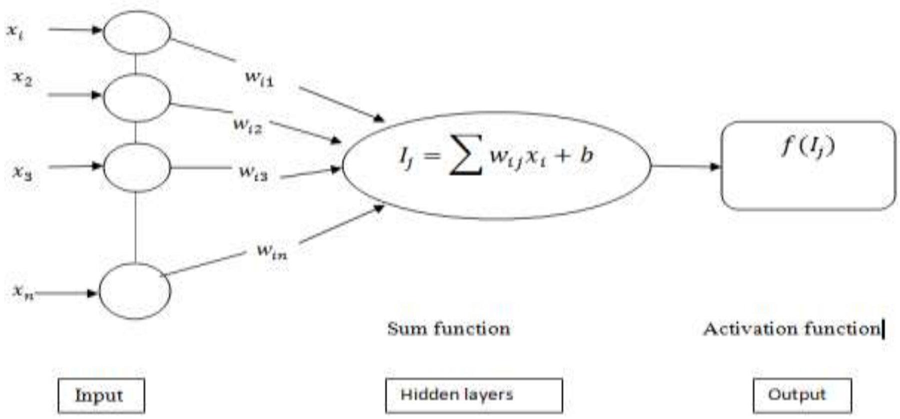

Figure 1. Typical neural network architecture

Experimental database collections and normalization

In this study, the main objective is to develop an ANNs model based on a comprehensive database to predict the mechanical properties (compressive strength) of self compacting concrete. For this objective, the first step needs to collect and select a large variety of pre-existing experimental data and construct a database reliable for training and testing samples and modeling with ANNs. A large number of databases with 179 cases, were collected and selected from sixteen different distinct sources in literature {20 data [2], 6 data [3], 28 data [4], 8 data [5], 12 data [6],42 data [7], 8 data [8],4 data [9], 3 data [10], 4 data [11], 4 data [12],11 data [13], 5 data [14], 11 data [15], 12 data [16] ,6 data [17]}, were used to construct the ANNs model. To measure the performance of the optimal model obtained by ANNs, it is necessary to use the testing data. The network needs to use the validation data in order to improve the construct network generalization after the training and testing phases were completed and to specify the generalization ability of the model chosen on data which they did not used in training in them and only in the range of input data. To obtain a consistent division, the data sets are divided randomly into three subsets: 149 data sets were allocated for the stages of training, approximately 83% of the database and remaining data sets were allocated about 30 data sets for the stages of testing, approximately 17% of the database. The range of the different input and output variables of total data sets used for building of ANNs model are summarized in Table 1.

Table 1. Model input and output parameter range

		Cement*	Water*	Silica *	SP %	FA*	CA*	Filler*	Compressive strength (MPa)
Mean	Training data	386.78	0.36	26.52	1.13	915.74	763.83	103.69	59.62
	Testing data	384.77	0.37	25.58	1.06	935.44	701.35	99.95	58.41
Maximum	Training data	600.00	0.50	150.00	6.00	1180.00	986.00	420.00	101.00
	Testing data	513.00	0.50	100.00	4.00	1160.00	917.00	390.00	85.30
Minimum	Training data	146.88	0.28	0.00	0.00	407.55	578.00	0.00	40.30
	Testing data	180.00	0.30	0.00	0.15	407.55	578.00	0.00	43.10

* Kg/m^3

Test for Mechanical properties - Compressive strength test

Compressive strength tests were performed on 150mmX150mmX150mm cubes using a compression testing equipment, as illustrated in Figure 2 (before failure) and 3 (Sample after failure). After being removed from the curing tank, the specimens were cleaned and carefully dried. The cube was then placed in the testing machine with the cast faces in contact with the platens. The stress was applied to the cube at a constant rate. To compare the strength of different SCC mixes, the compressive strength was determined after 28 days.

Figure 2. Sample before failure

Figure 3. Sample after failure

Figure 4. SCC mix specimen

Table 2. Experimental data sheet

Sr. No.	Cement*	w/b	Silica*	SP (%)	FA*	CA*	Filler*	Compressive strength (MPa)
1	350	0.4	20	1	960	600	220	60.15
2	250	0.35	18	1	1000	650	250	55.21
3	225	0.4	20	1	1050	650	200	47.73
4	300	0.35	60	1	950	600	240	78.76
5	400	0.3	10	1	950	670	150	63.52
* Kg/m^3								

3. RESULTS

ANNs model Development

Table 3. ANN model Learning Parameters

Parameters	
Number of hidden layers	2
No. of hidden neurons in left and right	8(left),7(right)
Learning rate	0.03
Momentum	0.5
Iterations	10000

Table 1 provides the statistics of data which was used for modelling. To examine the accuracy of result a line and bar chart graph is plotted between actual and predicted value in Figure 6-8. The results of performance evaluation parameters shows that ANN based model is R^2=0.9642, MAE=2.9501, RMSE=3.7021, RAE(%)=25.1982, RRSE(%)=26.5630 for training and R^2=0.9049, MAE=3.8729, RMSE=4.6531, RAE(%)=54.6531, RRSE(%)=51.8477 for testing and R^2=0.9891, MAE=3.8195, RMSE=6.6269, RAE(%)=47.8989, RRSE(%)=63.6111 for validating given the result best in using two hidden layer [left neuron(8),Right neuron(7)]. So the actual and predicated strength are obtained with minimum error.

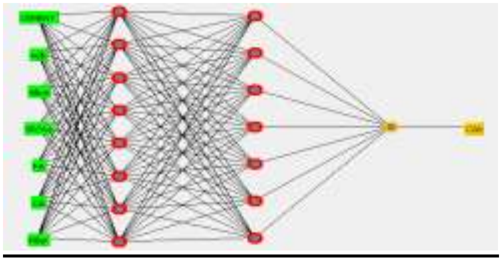

Figure 5. ANN with two hidden layers

The interpretable ANN model for 28 days compressive strength prediction as obtained for two [left neuron (8), Right neuron (7)] of the nodes in the hidden layer is-

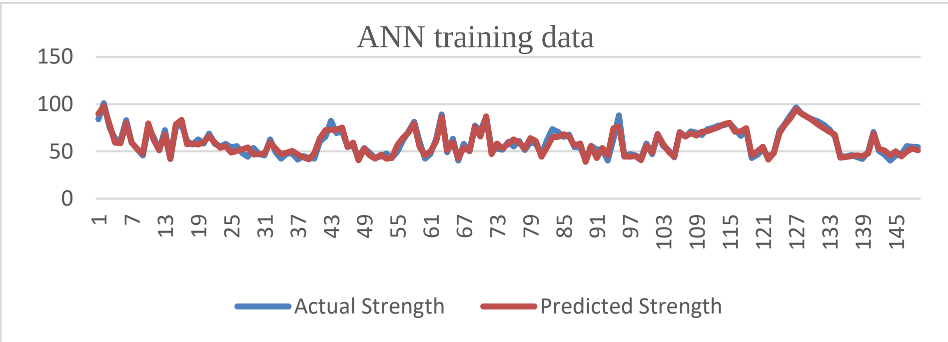

Figure 6. Training set

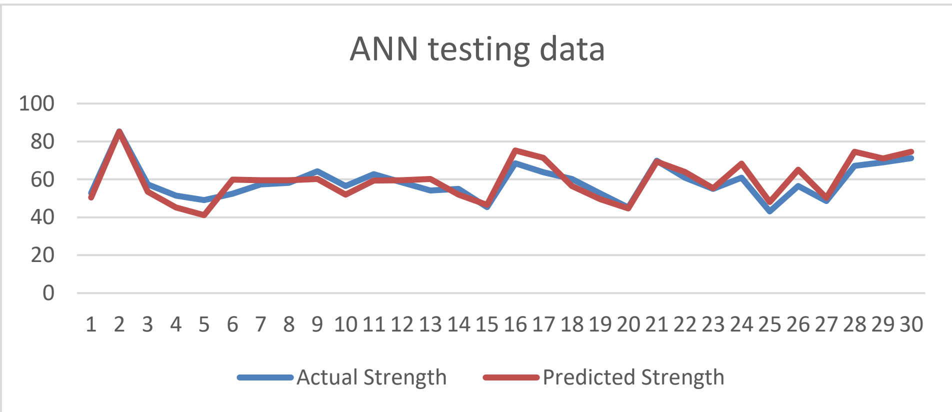

Figure 7. Testing set

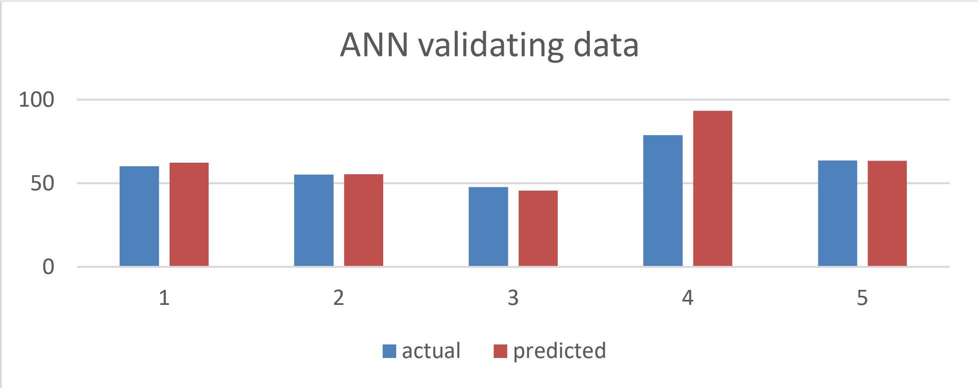

Figure 8. Validating set

Study of literature/research already published shows that generally the modal development using ANN involves the data obtained from another research [18] [19] . The novelty of the present study involves the actual data obtained from experimental work. The validation of the experimental data was also carried out keeping the various input parameters within the range for the model development.

4. CONCLUSIONS

In this Paper, Compressive Strength model using ANN is predicted for SCC including limestone powder, silica flume, and fly ash filler. Thus, following conclusions can be observed:

- The ANNs model proposed in this current study showed its ability to predict the CS of limestone powder, silica flume and fly ash filler self-compacting concrete and the best ANN's architecture of the proposed model is 7-8-7-1.
- A back-propagation, an ANN model can be trained to predict the CS of self-compacting concrete while relating the concrete mixes.
- In all phases of training, testing, and experimental validation, the modelling results are very good, coinciding well with the experimental values, demonstrating the accuracy of the proposed ANNs model. As a result, the ANNs model is an effective tool for predicting self-compacting concrete compressive strength.
- A parametric study was carried out to see the effect of each parameter considered in the proposed model on compressive strength. The results agreed with the literature.
- There are a lot of potential avenues for further works. In the future, the work can be extended by applying the ANN's for predicting several proprieties of SCC with limestone powder, silica flume and fly ash filler such as the workability, elasticity module, durability etc.

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