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Prediction of Compressive Strength of Self-Compacting Concrete (SCC) with Silica Fume Using Neural Networks Models

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Abstract

Self-Compacting Concrete (SCC) is a relatively new type of concrete with high workability, high volume of paste and containing cement replacement materials such as slag, natural pozzolana and silica fume. Cement replacement materials provide a wide variety of benefits such as lower cost, reduced consumption of natural resources, reduced carbon dioxide emissions and improved fresh and hardened properties. SCC is used in many applications such as sections with congested reinforcement and high rise shear walls and there is a need for the prediction of the performance of SCC used. Artificial Neural networks (ANN) are widely used in civil engineering for the prediction of the performance of some engineering materials such as compressive strength and durability. However, currently, studies on SCC containing silica fume are very rare. In this paper, an artificial neural networks (ANN) model is developed to predict the compressive strength of SCC with silica fume using the Levenberg-Marquardt back propagation algorithm based on a database from 366 experimental studies. The model developed was correlated with a nonlinear relationship between the constituents (input) and the compressive strength of SCC (output). To evaluate the predictive ability and generalize the developed model, other researchers' experimental results were compared with the model prediction and good agreements are found. A parametric study was conducted to study the sensitivity of the ANN proposed model to some parameters such as water/binder ratio and superplasticizer content. The model developed in this study can potentially be used for SCC compressive strength prediction with very acceptable results and a high correlation coefficient R^2=0.93**.** The developed model is practical, easy to use and user friendly.

Keywords: Self-compacting Concrete; Silica Fume; Prediction; Compressive Strength; Artificial Neural Networks.

1. Introduction

Concrete is the most used material worldwide in civil engineering structures because of its many advantages such as ease of molding, availability of constituent materials, high compressive strength and durability if well designed [1]. Self-Compacting Concrete (SCC) as a relatively new type of concrete has excellent deformability and passing ability under its own weight without any segregation. SCC differs from conventional concrete by its high fines content, high workability and higher water requirements and hence the prediction of its compressive strength is different than that of conventional concrete. Since its development in Japan in the late 1980's, significant progress has been made in SCC research and development. SCC is a solution to enhance the concrete workability as well as its strength. Mechanical properties, such as compressive strength, require selection of blend ratios, blend design specifications and economics

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of the cementitious materials used [2]. Compressive strength of concrete is widely used for the quality control of concrete on site. Compressive strength is generally obtained by testing concrete specimen after a standard curing of 28 days (Neville 1996).This property can be influenced by the use of alternative cementitious materials in concrete [3].

The use of supplementary cementitious materials (SCM) such as slag, natural pozzolana, fly ash (FA) and silica fume (SF) in the production of SCC is gaining widespread as it provides greater sustainability in construction projects by reducing CO_2 emission and reducing energy and cement consumption and hence lowering its environmental impact [4]. In addition, SCM improve the rheological properties at the fresh state and the strength and durability at the hardened state at long term. Silica fume is composed of very fine vitreous particles, which is a by-product of the smelting process in the silicon and ferrosilicon industry and is one of the most available SCM [5, 6]. The use of SF can produce both chemical and physical effects, which cause meaningful changes in the micro-structure of concrete such as reducing its permeability and increasing its compressive strength [5]. Compressive strength of SCC and other types of concrete with different cement replacement materials have been widely investigated. The compressive strength of SCC with silica fume and fly ash at different curing regimes was reported and the need for long term water curing proved [7]. Fly ash and slag have been found to significantly increase the compressive strength of SCC mixtures and that the presence of mineral admixtures improves the resistance to sulphate attack [8].

The compressive strength of SCC is a highly nonlinear function of the proportions its ingredients and there are no theoretical relationships between mixture proportioning and SCC strength and hence the need to use appropriate tools for their prediction based on its constituents at the time of design. Artificial neural network could be a good tool for this prediction. Artificial Neural Networks (ANN) is soft computing techniques developed to mimic the neural system of human being in learning from training patterns or data [9]. ANN modelling is getting more popular and has been commonly used in engineering tasks. ANN models can provide more accurate predictions of concrete properties and at the same time reduce the experimental work at the laboratory and on site. The main advantage of ANN is that no specific equation is needed as it relies only on the learning of input–output relation for any complex problem. The technique of neural networks automatically manages the relationships between variables and adapts its parameters based on the data used for their training [10]. This potential of ANN has been harnessed for wide applications in the field of civil engineering. ANN was used to estimate the main parameters needed in the design of concrete such as the compressive strength of hydrated lime cement concrete [11]. ANN was also used to evaluate the sulphate expansion of different types of cement using water/binder, cement content, FA or SF, C_3A, and exposure duration as input parameters [12]. Compressive strength and other properties of limestone filler concrete were also predicted using ANN modelling [7]. The concrete mix design incorporating natural pozzolans has also been modelled [13]. ANN models for some durability indicators such as carbonation depth and other properties of fly ash ordinary concrete and SCC was also studied [14, 15].

Many authors have proved that artificial neural networks are reliable computational models for the prediction of concrete strength. Saridemir [16]. Siddique et al. [17] developed an ANN model for a reasonable accurate predictions of the compressive strength of concrete with bottom ash as partial replacement of fine aggregates at different ages using eight input parameters. Chou and Fam [18] reported that combining two or more models produces the highest prediction performance of compressive strength of high performance concrete (HPC). It has been demonstrated that artificial neural networks and fuzzy logic approaches can be successfully used for the prediction of compressive strength of concrete with metakaolin in relatively short time and with little error rate. The 28 days compressive strength of no-slump concrete (NSC) was predicted using neural networks and found more feasible than the traditional regression models [19]. Neural network and fuzzy logic have also been proved as an alternative approach for the predicting of compressive strength of silica fume concrete [20]. ANN was also used to predict with reasonable accuracy the 28-days compressive strength of a normal and high strength SCC as well as high performance concrete (HPC) containing high volume fly ash over a wide range of compressive strengths of concrete from about 30 to 60 MPa [21].

Early evaluation of the compressive strength of SCC is important for design and application purposes in construction sites and ready mixed concrete plants. As strength is usually determined experimentally by destructive and non-destructive tests which are costly and time consuming, the prediction of compressive strength through mixture proportions by an ANN model can be useful for the concrete industry. Some work has been done for the prediction of the compressive strength of SCC but although SF is extensively used in SCC and ultra-high performance concrete, there are very limited investigations to predict the compressive strength from its constituents for SCC with SF.

The aim of this investigation is to develop a user friendly ANN model for predicting the compressive strength of SCC incorporating silica fume. After a brief description of the neural network model used, the database collection and analysis was described. Then, the training of the ANN model was carried out on a set of experimental data considering several parameters such as water/binder ratio, binder content, silica fume, sand content (S), gravel content (G), superplasticizer (Sp) and curing age (A). These parameters were used as experimental input variables while the experimental compressive strength (CS) property was used as an output. The validity of the model was then checked. Finally, a parametric analysis and comparison were carried out between the experimental and the ANNs predicted results for performance evaluation of the ANNs model.

2. Description of Neural Network Models

ANN is a very powerful computational tool for modelling complex non-linear relationships inspired by biological neural networks [10]. There is an increasing number of different types of ANN and learning algorithms such as deep learning with convolutional neural networks [22] and the most used and well-known training algorithms for the multilayer perceptron is the back-propagation multi-layer perceptron (BPMLP). The technique is based on a gradient descent technique. It is used for minimizing the error for a particular training pattern by adjusting the weights by a small amount at a time [15, 23]. This technique is widely used in civil engineering applications [15]. In a BPMLP, the arrangement of neurons or nodes is in the form of one input layer, one output layer and hidden layers. All the neurons in each layer have connections to all the neurons in the next layer as depicted in Figure1.

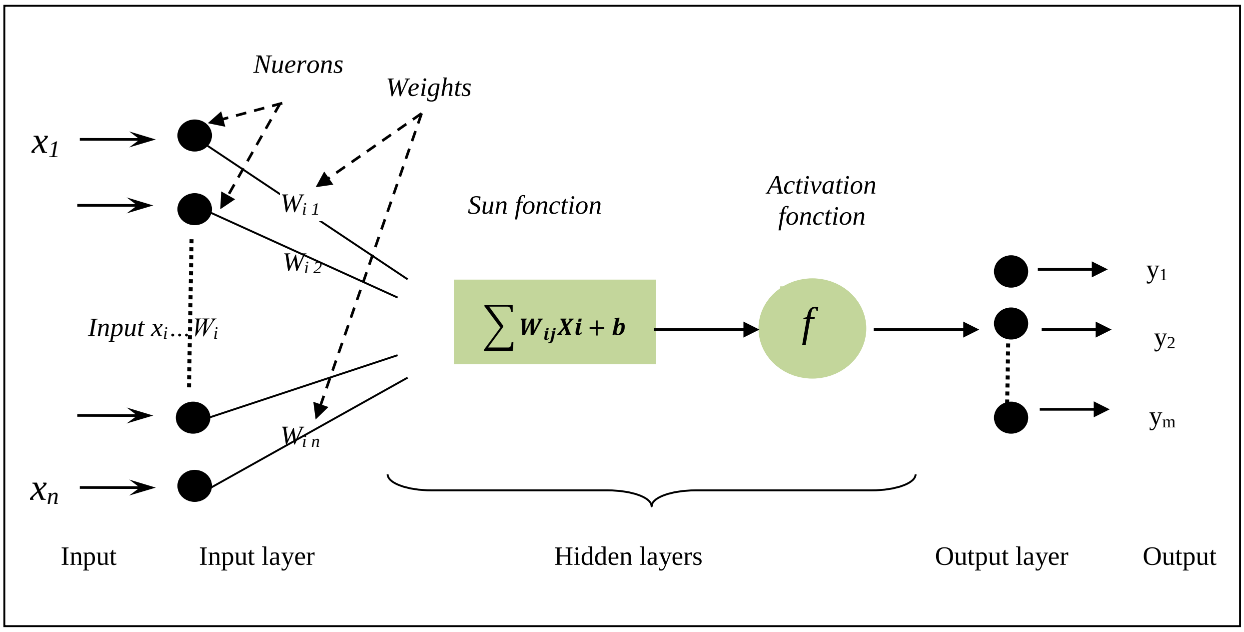


Figure 1. Typical neural network architecture

At each neuron, the weights are values that express how much effect the input will have on the output. The total number of nodes in the input and output layers represent the number of input and output variables. The ideal number of nodes in the hidden layer is determined by trial and error as there is no known rule for selecting the number of nodes in a hidden layer, which is a network dependent [15]. The activation function determines the output value of each neuron. A non-linear activation function is generally used for all neurons with full connection that maps the weighted inputs to the output of each neuron. Two non-linear sigmoid activation functions are used as presented in Figure1 [16, 23].

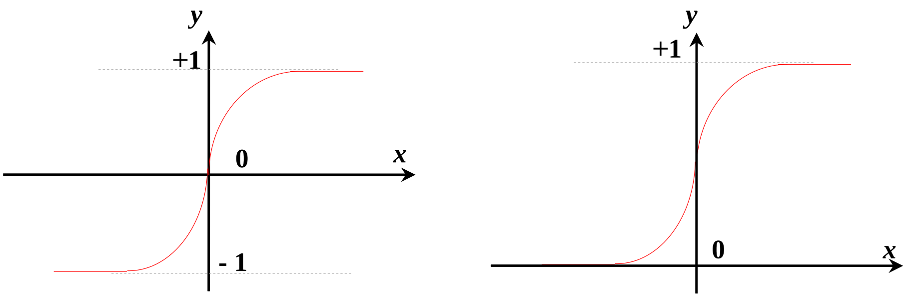


Figure 2. Tan-Sigmoid and logistic Transfer function

The first is a hyperbolic tangent function that ranges from -1 to 1, while the second is a logistic, with similar shape but ranges from 0 to 1. The output of the neuron is y and x is the weighted sum of the input connections. To train the network, a training algorithm is used allowing the ANN to develop a relationship between the inputs and outputs [23]. The training is an iterative process that stops when a designed error is reached by adjusting the network weights. The training related parameters such as the learning rate, momentum and stopping time are the most important parameters that should be selected during the training in order to increase the model speed convergence and prevent it from over fitting.

The network performance is determined by the root mean square error (RMSE) and the absolute fraction of variance (R2) using respectively Equations 1 and 2. In addition, Equation 3 determines the mean absolute percentage error (MAPE):

$$RMSE = \sqrt{MSE} = \sqrt{\left(\frac{1}{P}\right) * \sum_j (t_j - o_j)^2} \tag{1}$$

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \tag{2}$$

$$MAPE = \frac{1}{P} \sum_j \left(\left| \frac{o_j - t_j}{o_j} \right| 100 \right) \tag{3}$$

Where t_j is the target value of jth pattern (corresponds to predicted result in this work), o_j is the output value of jth pattern (corresponds to experimental results in this work), and P is the number of patterns. The network is able to give the output for any other input not included in the database when the training process is complete [23].

3. ANN-based Prediction Model of SCC Compressive Strength and Validation

The main purpose of this study is to develop ANN models for predicting the compressive strength based on mixture proportioning of SCC with SF. The development process of this ANN model was divided into three main sections. The first section concerns the collection and analysis of data on SCC with silica fume. The second is devoted to selecting suitable ANN architectures and optimal training parameters including performance function, learning algorithm and execution time. In the third and last section, a comparison with other existing experimental data was carried out to validate the proposed ANN models and assess their performances. The research methodology is summarized in Figure 1.

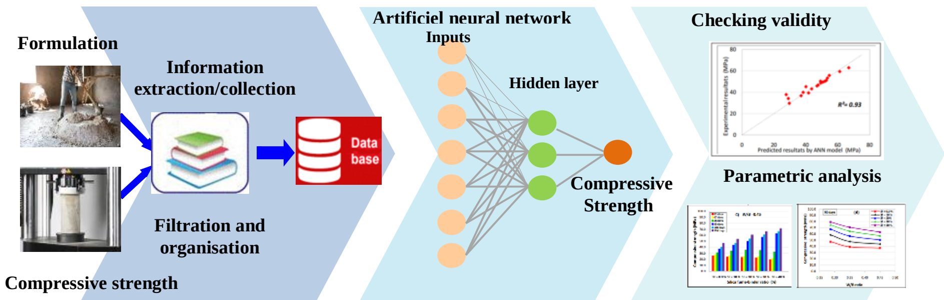


Figure 3. Flowchart of research methodology

3.1. Database Collection and Analysis

The database of compressive strengths of SCC with SF was assembled from different research projects. A total number of 366 SCC compositions (Table 5) were collected from 25 sources published between 2004 and 2020 (Figure 4) for building the ANN model (training testing and checking).

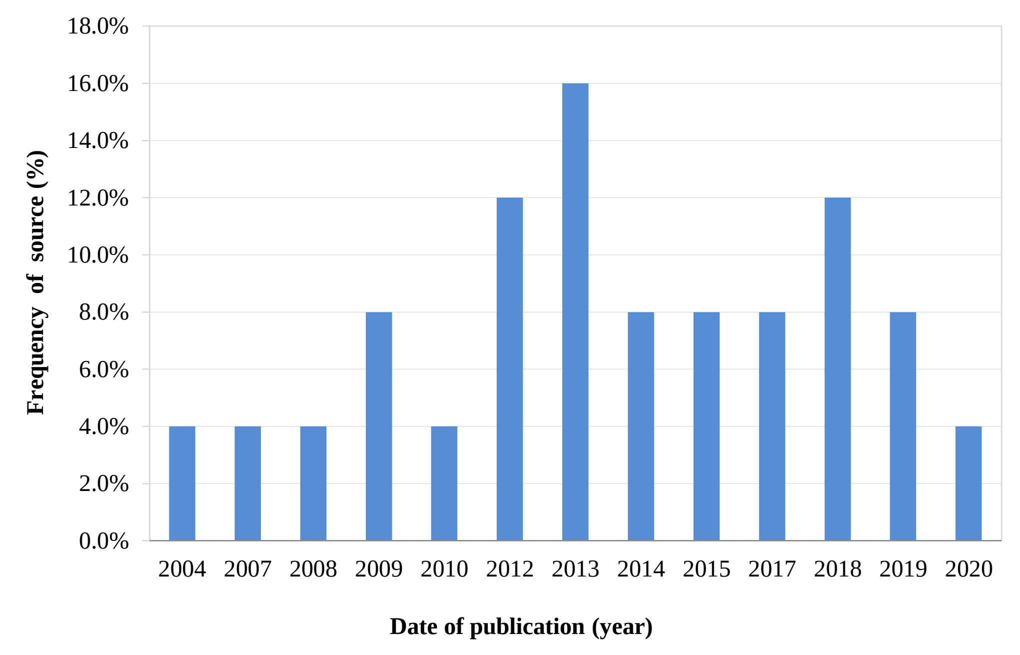


Figure 4. Frequency of sources in different date of publication

During the evaluation and selection of the data, some of the mixes were ignored due to inaccurate or insufficient information or due to special curing conditions and larger than 20 mm size aggregates. The variables of the data base are quantities for one cubic meter of concrete mix constituents (binder content, silica fume, fine aggregates, coarse aggregates, superplasticizer) and age of testing as input dataset with the corresponding compressive strength value at different ages as output dataset. The compressive strengths tests were performed on cubic specimens of (10×10×10) cm and (15×15×15) cm, and cylindrical specimens of (10×20) cm and (15x30) cm. All of compressive strength results were converted into equivalent 15x30 cylindrical using the following empirical formulas (Equations 4 and 5) [24].

$$f_\alpha = f_{10}\left[0.58 + 0.42\left(\frac{10}{\alpha}\right)^{1/3}\right] \tag{4}$$

$$f_{cyl} = f_{15}\left[0.76 + 0.2\log_{10}\left(\frac{0.95 f_{10}}{19.6}\right)^{1/3}\right] \tag{5}$$

Where f_α is the cube compressive strength, α is the cube size, f_{10} and f_{15} are 10 cm and 15 cm cube compressive strength respectively, f_{cyl} is the cylinder compressive strength.

Table 1, shows the boundary values for input and output variables used in the ANN model. Table 2 shows that the input parameters are distributed in different ranges in a homogeneous form for training the mode l.

Table 1. Boundary range of inputs and output of model

	Minimum	**Maximum**	**Average**
Inputs variables			
Water to binder ratio "W/B"	0.22	0.51	0.38
Binder "B" (kg/m³)	359	600	702
Silica fume (kg/m³)	0	250	46
Fine aggregate (kg/m³)	680	1166	903
Coarse aggregate (kg/m³)	595	1000	817
Superplasticizer (kg/m³)	1.30	15.00	7.21
Age of specimen (days)	1	270	
Outputs variable			
Compressive strength (MPa)	21.12	106.60	54.01

Table 2. Distribution of inputs in the data base

Water/binder		Binder		Silica fume		Fine aggregate		Coarse aggregate		Superplasticizer	
Rang	Freq.	Rang (kg/m³)	Freq.	Rang (kg/m³)	Freq.	Rang (kg/m³)	Freq.	Rang (kg/m³)	Freq.	Rang (kg/m³)	Freq.
0.20-0.25	1	350–400	8	0–30	43	650–750	5	550–650	11	0–3	7
0.26–0.30	4	401–450	26	31–60	29	751–850	22	651–750	21	3.1–6	20
0.31–0.35	17	451–500	15	61–90	17	851–950	48	751–850	14	6.1–9	61
0.36–0.40	57	501–550	43	91–120	10	951–1050	14	851–950	49	9.1–12	9
0.41–0.52	21	551–600	8	121–250	1	1051–116	11	951–1050	5	12.1–15	3

3.2. ANN Architectures and Training Parameters

In this research, to provide an ANN model with good generalization capability, the databases were randomly divided into three datasets: 70 % of input values are considered as training, 15 % as validating, and the remaining 15 % as testing. In order to achieve the optimum data division in this study, several random combinations of the training, testing, and validation sets were tried until three consistent datasets were obtained as shown in Table 3.

For conducting ANN model, a MatLab program was implemented using neural network toolbox functions (R2016b). The back-propagation algorithm was employed to train and test the ANN model consisting of three adjacent layers: one input layer, one hidden layer, and one output layer and each layer is composed of a number of neurons. The number of neurons in input and output layers corresponds to variables of data and target output respectively. The number of hidden layers and their size were selected after several attempts in order to achieve the desired result since there is yet no theory or rule for determining the number of hidden layers to construct the network [13]. Subsequently, seven (07) neurons in the input layer representing the variables of data, three (03) neurons in the hidden layer and one (01) neuron in the output layer corresponding to the compressive strength at different ages were selected for the ANN model. The following variables were used as input parameters to build and train the model namely: amount of the water-to-binder ratio (W/B), binder content (B), silica fume (SF), fine aggregates (FA), coarse aggregates (CA), superplasticizer (SP) and age of curing. The corresponding model is given graphically in Figure. 5.

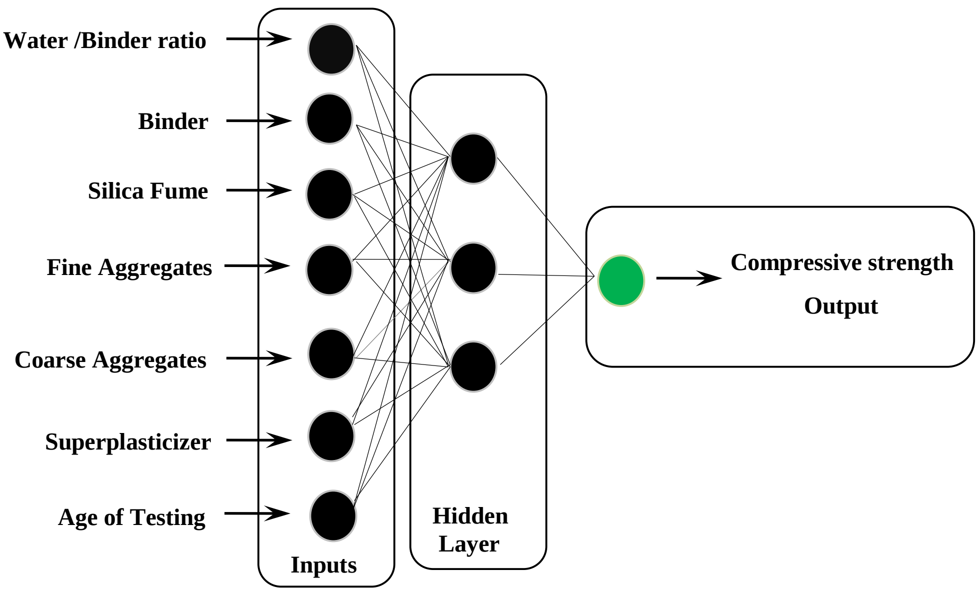


Figure 5. Structure of the developed ANN model

After different combinations of the two proposed nonlinear activation function, the nonlinear activation function “tansig” of MATLAB's was used for all neurons as shown in Equation 6.

$$Tanh(y) = \frac{(1 - e^{-2x})}{(1 + e^{-2x})} \tag{6}$$

This function is highly recommended as it is the fastest back propagation algorithm as compared to other algorithms. By minimizing the performance function (mean square error) during the training process, a maximum number of epochs (learning cycles) were reached. All the training parameters for each ANN model including learning rate, momentum rate, training epoch and mean square error are summarized in Table 3.

Table 3. The values of ANN parameters models used in this research

ANNs parameters	
Train function	Trainlm (Levenberg–Marquardt)
Transfer function	Tansig "tan-sigmoid" (no linear function)
Performance function	MSE (mean square error)
Train epochs	1000
Error after learning	0.001
Divide function	Dividerand
Learning rate	0.100
Momentum rate	0.001
Goal	0.001
Show	5

The criterion to select the optimal architecture and the best learning parameters of ANN models developed in this research, involves minimizing the error, maximizing the correlation and conducting a parametric analysis for exploring the most influential factors of SCC mixtures on the ANN model prediction. Accordingly, the prediction results are compared with the experimental data showing high correlation and providing high estimation accuracy (Figure. 6).

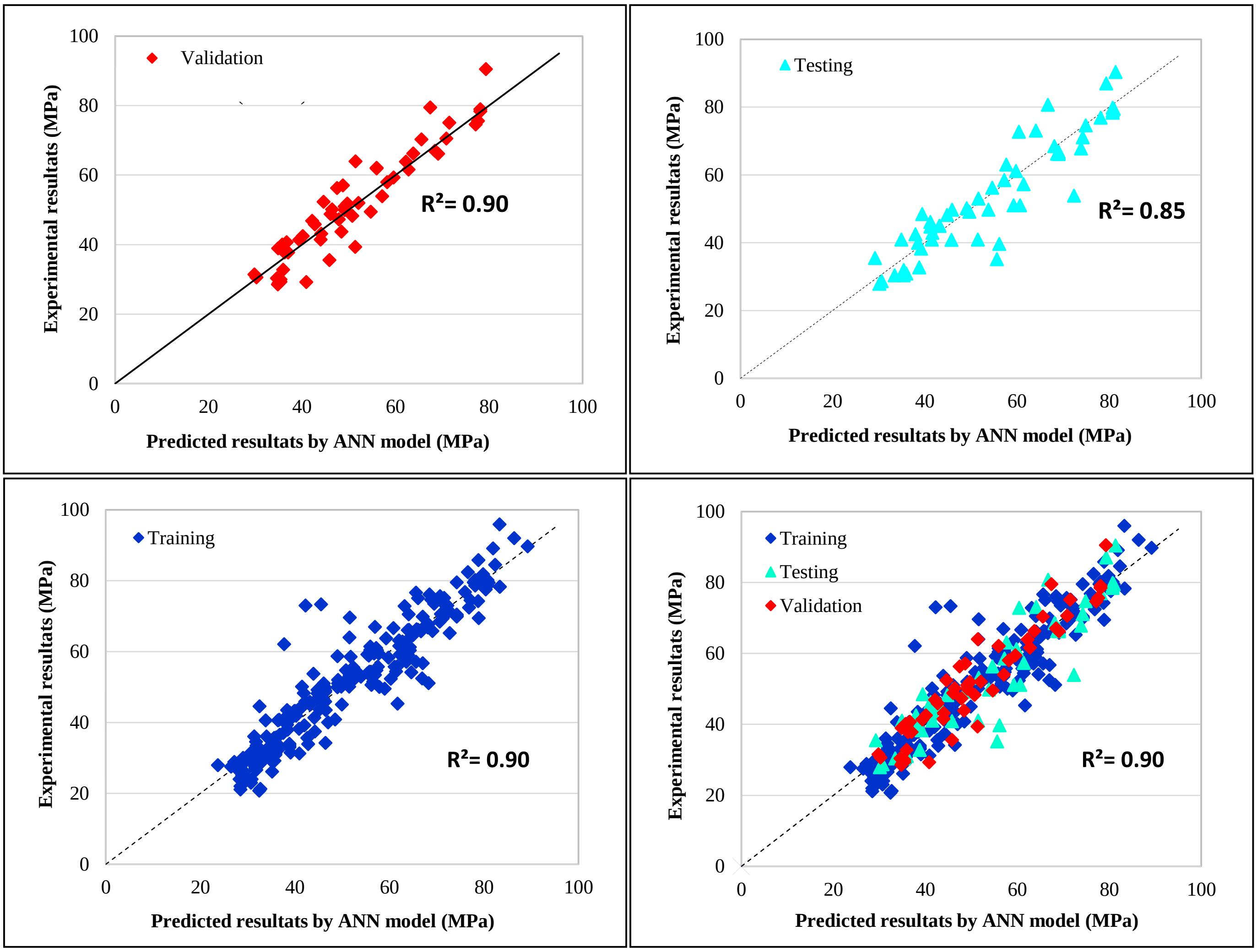


Figure 6. Correlation cohered between experimental and predicted compressive strength for SCC (a) Validation, (b) Testing set, (c) Training set, (d) All sets

3.3. Checking Validity of the ANN Model

In this section, the generalization performance of the well-trained ANN model was evaluated in order to check its predictive ability and accuracy with unseen data within the range of the input parameters used in the training process. Therefore, additional experimental results obtained from other researchers excluded from the training data were considered. A total of 19 SCC mixtures collected from three different sources [25-27] were presented to the ANN model developed and the network was required to predict the compressive strength associated with each mixture. Moreover, in table 4, the accuracy was measured based on the mean absolute percentage error (E) as a potential solution to improve the interpretability of the results prediction using Equation 7 [25]:

$$E(\%) = ABS\left(\frac{O_{Exp} - O_{ANN}}{O_{Exp}}\right) \times 100 \tag{7}$$

Where O_{Exp} is the experimental result, O_{ANN} is the predicted result calculated by the developed model.

According to table 4, the average relative errors between the predicted and the experimental results were quite low (4.94 %) though slightly higher than that reported for the prediction of compressive strength of concrete with natural pozzolana [23]. From figure 5 and table 4, it can be concluded that the predicted results obtained from the ANNs model are in agreement with those of the measured experimental results.

The comparison between the obtained results by the developed ANN model and the validation of new data records is shown in Figure 6 and in Table 4. According to Figure 7, the testing data points (experimental results) are located along the equity line within the cluster formed by training data points (predicted results), with perfect correlation (R^2=0.93).This is comparable to the coefficients of correlation reported for the prediction of the compressive strength of concrete with natural pozzolana which was 0.93 for the hybrid system and 0.83 for the ANN model [23] and for the compressive strength of SCC with fly ash which was 0.95 [15]. A correlation coefficient of 0.919 was achieved for the prediction of 28 days compressive strengths using ANN for SCC containing bottom ash as partial replacement of fine aggregates [17]. Accordingly, the compressive strength of SCC containing silica fume is predicted with very satisfactory results using the proposed ANN model in this research. The results of the developed model are also comparable to other artificial intelligence methods such Multivariate Adaptive Regression Splines (MARS) and Gene Expression Programing (GEP) which were used for the prediction of the compressive strength of SCC with SF using 117 datasets where the comparison between the predicted compressive strength and the experimental results showed a correlation coefficient of 0.98 and 0.83 for MARS and GEP methods respectively [28].

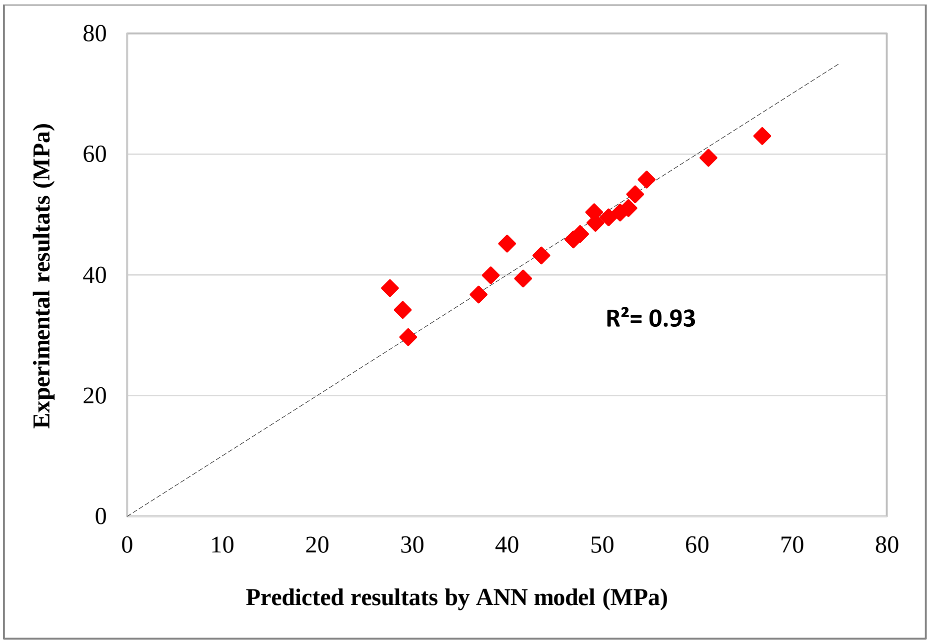


Figure 7. Comparison between the ANN results and experimental results

Table 4. Relative errors of the predicted results of ANN model and experimental researcher's results

Author	Year	Age (day)	Exp.	ANN	E (%)
Tahwia *et al* [25]	2018	7	29.70	29.60	0.34
		7	34.20	29.03	15.12
		7	37.80	27.67	26.80
		28	43.20	43.61	0.95
		28	45.90	47.00	2.40
		28	50.40	49.18	2.42
		90	55.80	54.72	1.94
		90	59.40	61.21	3.05
		90	63.00	66.88	6.16
Dinesh *et al* [26]	2017	28	46.77	47.70	1.99
		28	48.62	49.30	1.40
		28	49.53	50.70	2.36
		28	50.31	51.90	3.16
		28	51.05	52.80	3.43
		28	53.34	53.50	0.30
Syed., A. [27]	2009	28	36.77	37.00	0.63
		28	39.93	38.30	4.08
		28	45.20	40.00	11.50
		28	39.39	41.70	5.86
			Average error		**4.94%**

4. Parametric Analysis of ANN Developed Model

A parametric study was conducted to evaluate the effect of the operating parameters affecting SCC compressive strength as this allows the developed ANN model to be used as an effective prediction tool. The sensitivity of the compressive strength predicted by the ANN model as output parameters to variations of some of the main input parameters was evaluated by examining the effect of changing one parameter whereas all others were kept constant. Consequently, this yields functional relations between the compressive strength and the other mix design parameters (water-to-binder ratio, amount of binder, silica fume, fine aggregates, coarse aggregates, superplasticizer and curing age) . The simulation results and discussion are shown as follows.

4.1. Effect of Water-binder Ratio and SF Content on Compressive Strength at Different Ages

The water-binder (w/b) ratio is the basic parameter that governs the SCC compressive strength. Fig. 8 shows the influence of the w/b (0.30, 0.35 and 0.45) on the compressive strength of SCC with increasing amounts of SF (from 0 to 40%) at different ages (3, 7, 28, 90, 180 and 365 days). As seen from these curves, the values of compressive strength decrease with increasing w/b ratio at all ages with different dosages of SF. A similar trend was reported earlier by other researchers [29-32] in which this negative effect can be explained by an increase of the volume of capillary pores leading to a reduction in compressive strength [33]. On the other hand, at early-age (3 and 7 days), the compressive strength decreases with increasing SF content. The compressive strength of the control SCC (SF = 0.0 %) is always higher than that of SCC with different dosages of SF. Similar results have been reported by other authors [33-35]. The loss of the compressive strength increased from 20 % to 35 % with increasing SF from 0 % to 40 %. This could be caused by the dilution effect resulting from the addition of silica fume and the multiplication of the pseudo crystals of Portlandite. However, the pozzolanic reaction takes place very quickly, and consumes the Portlandite produced by the nucleation hydrogen [35, 36]. As shown in Figures 8 and 9, at the age of 28, 90, 180 and 365 days, the values of compressive strength of all SCC increased with increasing SF content. For example, at 0.35 w/b ratio, when varying SF content from 0 to 40%, compressive strength increases by about 9 to 18% compared to that of control concrete at 90 days. The increase in compressive strength of SF mixtures could be explained by the higher pozzolanic activity of the silica fume [37, 38].

4.2. Effects of Superplasticizer on the Compressive Strength

Superplasticizer (SP) is an essential ingredient in the production of the SCC. Although, superplasticizers are added to concrete mainly to provide a better workability by the dispersion of agglomerated cement particles without increasing the water content, they can be used as water reducing admixtures and hence improve the compressive strength and durability of concrete [39]. The variation of the compressive strength at different ages with superplasticizer dosages (from 0 to 9 kg) for different dosage of SF is shown in Figure 10. According to this figure, it should be noted that increasing the content of superplasticizer has a positive effect on compressive strength at all ages, as reported earlier by Neville [40].

5. User Interface Development of the ANN Model

Designers in the laboratory or on site need software and computing tools that are more robust and user friendly, for easy applications by non-specialist engineers. In this study, considerable effort and time were devoted to make the model easy to use, user friendly and with visual interface by using the MATLAB based (R2016b). Numerical values of water/binder ratio, amount of binder, silica fume, aggregates, and superplasticizer and the age of test can be entered as shown in Figure 11. The compressive strength of SCC is then displayed directly by clicking the predict button.

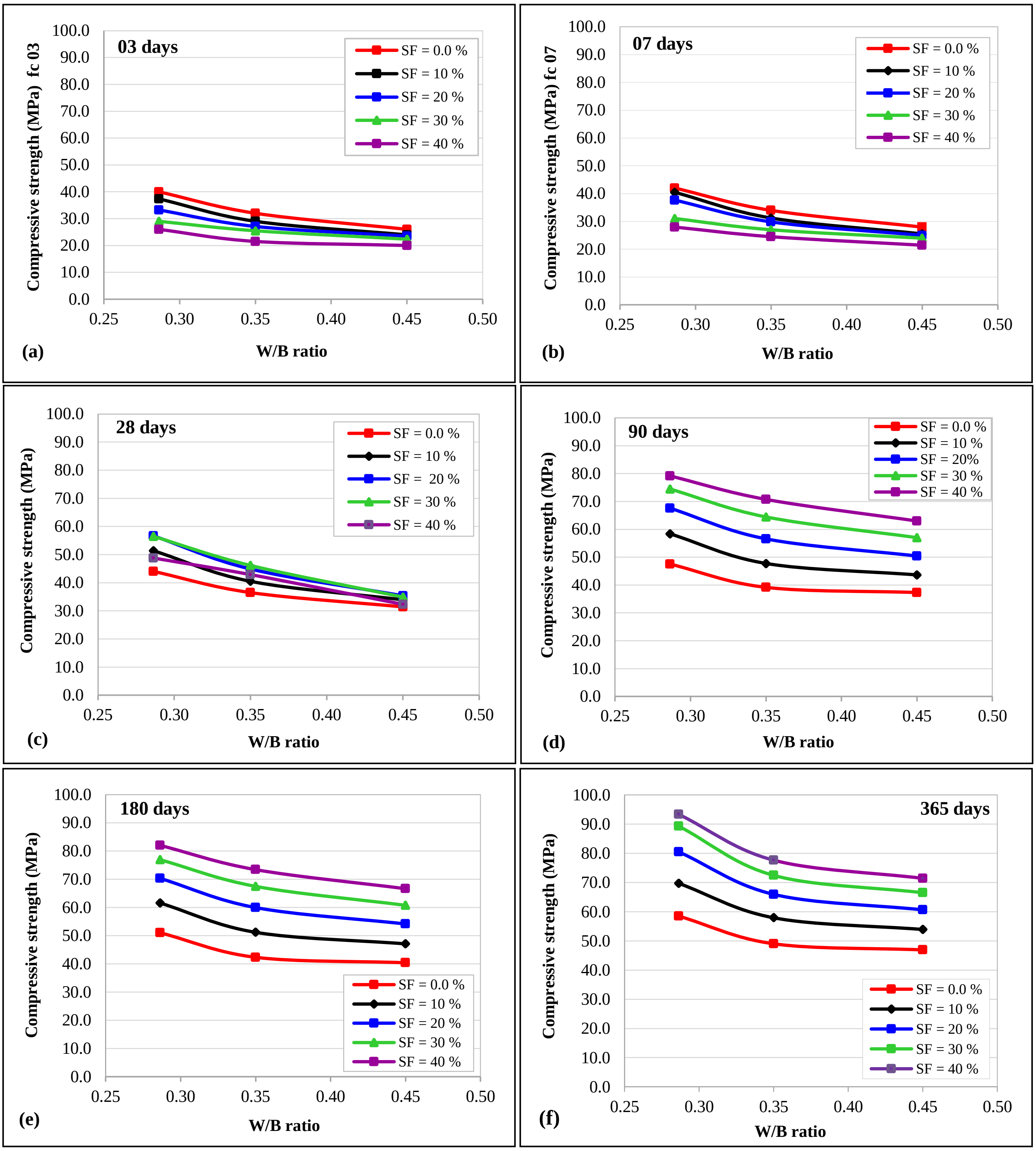


Figure 8. Effect of w/b ratio on ANN prediction of the compressive strength of SCC with different amounts of SF at various ages of (a) 3 days, (b) 7 days, (c) 28 days, (d) 90 days, (e) 180 days and (f) 365 days

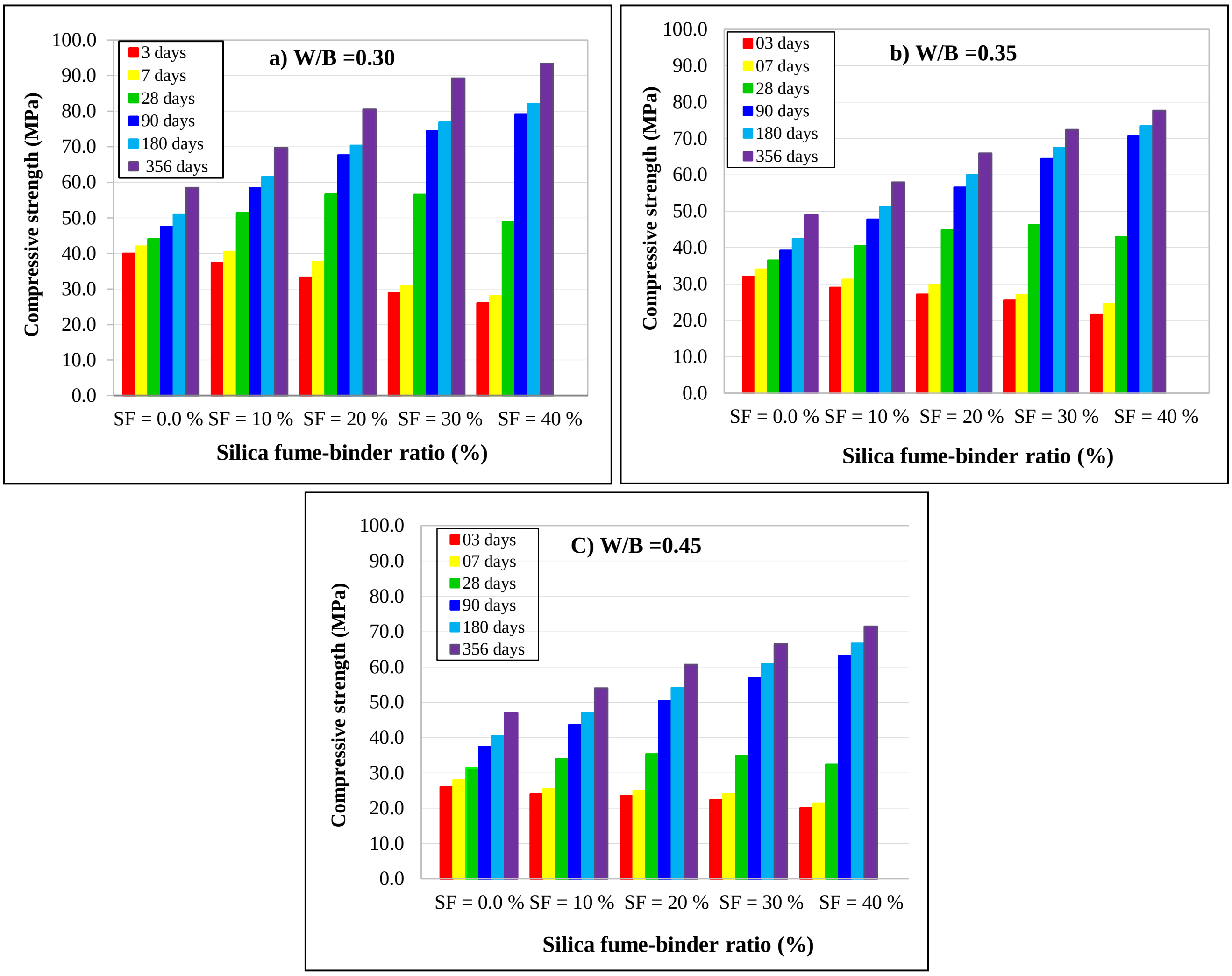
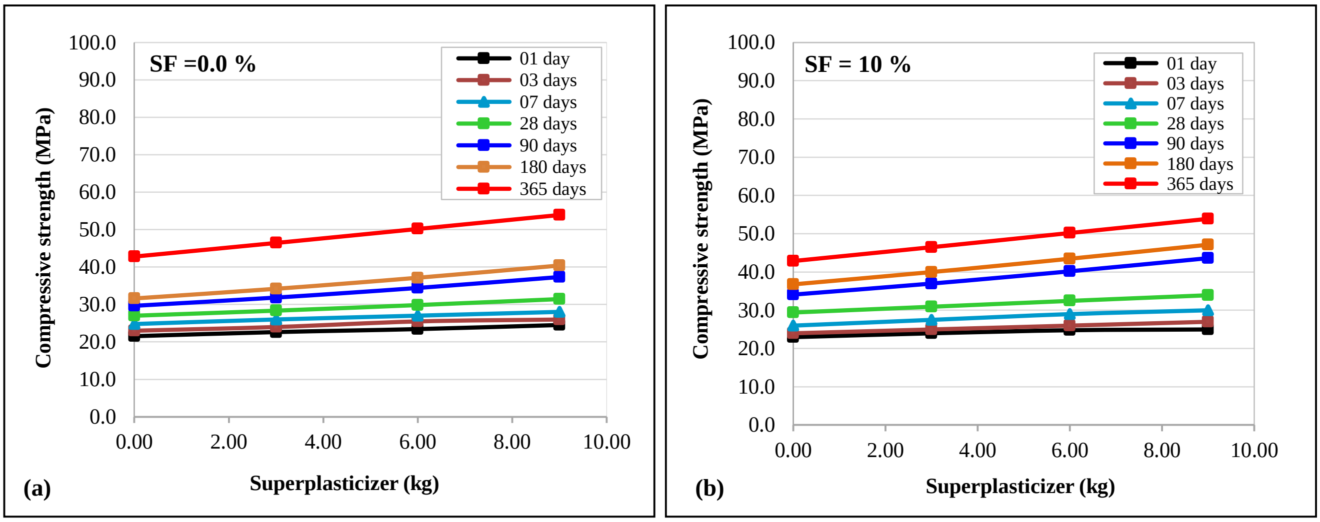


Figure 9. Effect of age on the compressive strength at different w–b ratios w/b = 0.3, w/b = 0.35, w/b = 0.45



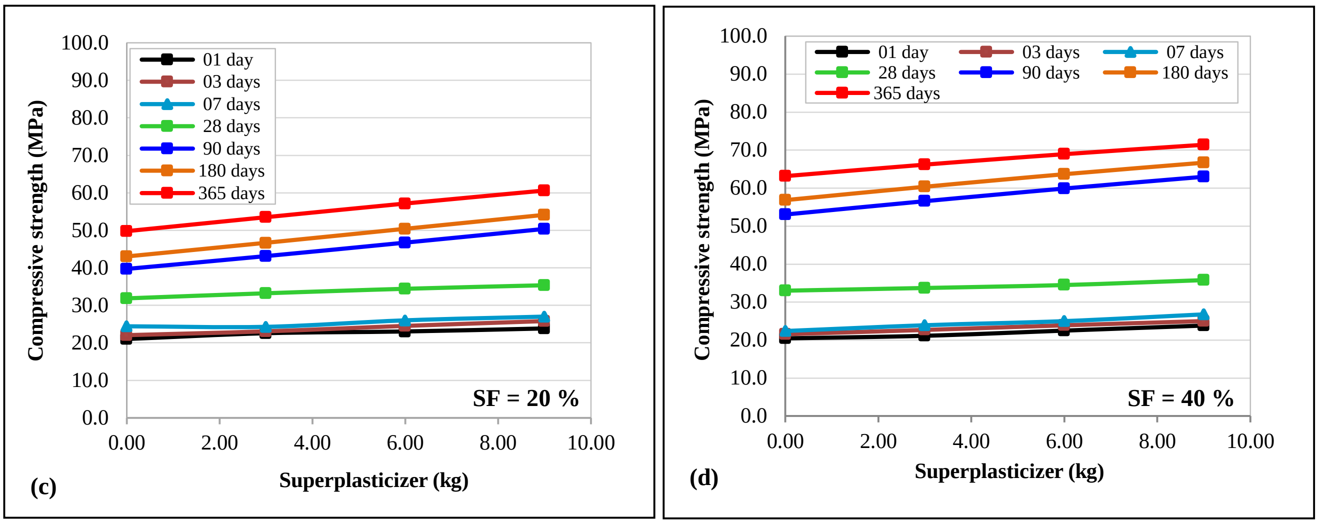


Figure 10. Effect of superplasticizer content on SCC compressive strength for various ages at SF content of (a) 0.0%, (b) 10%, (c) 30% and (d) 40%

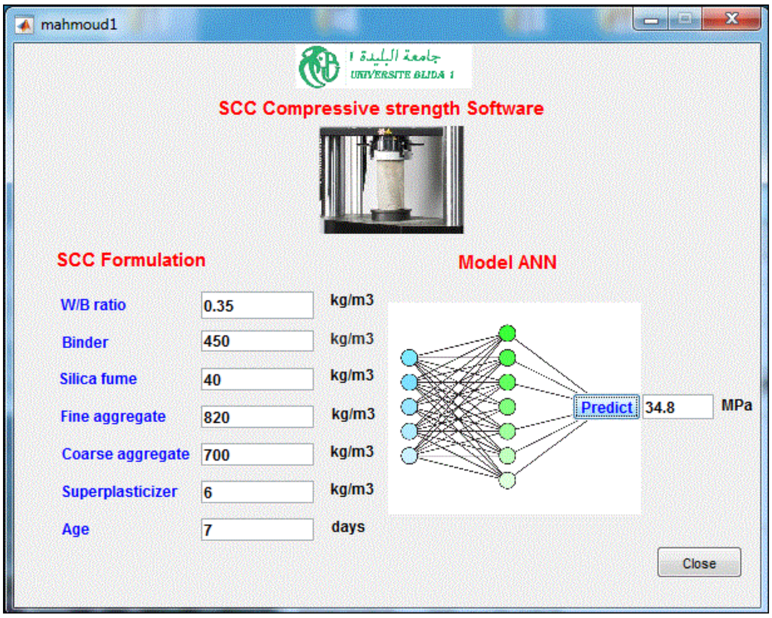


Figure 11. ANN interactive graphical user interface

6. Conclusions

In this study, an artificial neural network model was built to predict with good accuracy the SCC compressive strength with silica fume as cement replacement material. For this model, feed-forward Backpropagation network trained by Levenberg–Marquardt algorithm was used. The results obtained from this paperled to the following conclusions:

- The SCC compressive strength model based on the ANN using the back-propagation algorithm is more accurate than the model based on other ANN training algorithms. The proposed model gave very acceptable results with a high correlation coefficient R^2 equal to 0.93;
- The predicted results coincide well with the experimental values in all phases of training, testing and validation clarifying the accuracy of the proposed ANNs model;
- The developed model was able to evaluate the effect of all SCC constituents (binder, SF content, fine aggregates, coarse aggregates and superplasticizer) as well as water/binder ratio on the compressive strength of SCC with SF. The simulation results are in agreement with previous literature findings;
- The proposed ANN model is a very convenient mix design method that for concrete mix designers to estimate the compressive strength of SCC based only on its constituents at the time of design. The simulation of experiments reduces time and cost;

- An improvement in compressive strength of SCC with the use of SF as a partial replacement of cement is shown based on ANN model. The model prediction results demonstrate that it is feasible to use SF to produce normal strength SCC;
- The developed model is characterized by being practical, accurate, user friendly and easy to use;
- The developed model is limited to SCC with SF and further work is needed to investigate the effect of fiber reinforced SCC as well as the workability (slump flow, the V-funnel time and the L-box ratio), elasticity modulus and durability indicators such as water and oxygen permeability of SCC with silica fume.

7. Declarations

7.1. Author Contributions

Serraye, M.: Data curation, investigation, writing original draft. Kenai, S.: Conceptualization, supervision, funding acquisition, methodology, formal analysis, validation, writing-review, and editing. Boukhatem, B.: Validation, supervision, writing-review & editing.

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.3. Funding

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7.4. Conflicts of Interest

The authors declare no conflict of interest.

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Appendix I: Data sources

Author	Year	Ratio W/B	Binder	Silica fume	Fine aggregate	Coarse aggregate	Superplasticizer (SP)	Age (day)	Compressive strength (MPa)
Benaicha et al. [41]	2015	0.37	520	0	890	900	7.80	1	29.2
		0.37	520	0	890	900	7.80	1	29.6
		0.37	520	0	890	900	7.80	1	30.0
		0.37	520	0	890	900	7.80	1	28.6
		0.37	520	0	890	900	7.80	1	29.5
		0.37	520	25	890	900	7.80	1	35.6
		0.37	520	25	890	900	7.80	1	34.8
		0.37	520	25	890	900	7.80	1	34.6
		0.37	520	25	890	900	7.80	1	34.6
		0.37	520	25	890	900	7.80	1	34.0
		0.37	520	47	890	900	7.80	1	32.6
		0.37	520	47	890	900	7.80	1	32.0
		0.37	520	47	890	900	7.80	1	32.4
		0.37	520	47	890	900	7.80	1	32.8
		0.37	520	47	890	900	7.80	1	32.0
		0.37	520	68	890	900	7.80	1	32.0
		0.37	520	68	890	900	7.80	1	31.2
		0.37	520	68	890	900	7.80	1	31.0
		0.37	520	68	890	900	7.80	1	30.8
		0.37	520	68	890	900	7.80	1	31.3
		0.37	520	87	890	900	7.80	1	31.2
		0.37	520	87	890	900	7.80	1	30.0
		0.37	520	87	890	900	7.80	1	30.4
		0.37	520	87	890	900	7.80	1	32.0
		0.37	520	87	890	900	7.80	1	29.4
		0.37	520	104	890	900	7.80	1	30.4
		0.37	520	104	890	900	7.80	1	30.6
		0.37	520	104	890	900	7.80	1	29.9
		0.37	520	104	890	900	7.80	1	30.8
		0.37	520	104	890	900	7.80	1	30.4
		0.37	520	120	890	900	7.80	1	30.4
		0.37	520	120	890	900	7.80	1	30.6
		0.37	520	120	890	900	7.80	1	29.9
		0.37	520	120	890	900	7.80	1	30.8
		0.37	520	120	890	900	7.80	1	30.4
		0.37	520	0	890	900	7.80	7	33.6
		0.37	520	0	890	900	7.80	7	34.0
		0.37	520	0	890	900	7.80	7	33.2
		0.37	520	0	890	900	7.80	7	32.8
		0.37	520	0	890	900	7.80	7	33.0
		0.37	520	25	890	900	7.80	7	44.0
		0.37	520	25	890	900	7.80	7	44.2
		0.37	520	25	890	900	7.80	7	46.2
		0.37	520	25	890	900	7.80	7	44.8
		0.37	520	25	890	900	7.80	7	44.0
		0.37	520	47	890	900	7.80	7	45.0
		0.37	520	47	890	900	7.80	7	45.8
		0.37	520	47	890	900	7.80	7	45.0
		0.37	520	47	890	900	7.80	7	45.4
		0.37	520	47	890	900	7.80	7	45.0
		0.37	520	68	890	900	7.80	7	46.8
		0.37	520	68	890	900	7.80	7	46.4
		0.37	520	68	890	900	7.80	7	48.2
		0.37	520	68	890	900	7.80	7	48.2
		0.37	520	68	890	900	7.80	7	49.2
		0.37	520	87	890	900	7.80	7	49.8
		0.37	520	87	890	900	7.80	7	49.6
		0.37	520	87	890	900	7.80	7	49.0
		0.37	520	87	890	900	7.80	7	49.0
		0.37	520	87	890	900	7.80	7	48.6
		0.37	520	104	890	900	7.80	7	50.2
		0.37	520	104	890	900	7.80	7	48.6
		0.37	520	104	890	900	7.80	7	48.8

Author	Year	Ratio W/B	Binder	Silica fume	Fine aggregate	Coarse aggregate	Superplasticizer (SP)	Age (day)	Compressive strength (MPa)
		0.37	520	104	890	900	7.80	7	49.8
		0.37	520	104	890	900	7.80	7	49.0
		0.37	520	120	890	900	7.80	7	50.2
		0.37	520	120	890	900	7.80	7	48.6
		0.37	520	120	890	900	7.80	7	48.8
		0.37	520	120	890	900	7.80	7	49.8
		0.37	520	120	890	900	7.80	7	49.0
		0.37	520	0	890	900	7.80	28	52.0
		0.37	520	0	890	900	7.80	28	51.0
		0.37	520	0	890	900	7.80	28	51.0
		0.37	520	0	890	900	7.80	28	50.2
		0.37	520	0	890	900	7.80	28	50.0
		0.37	520	25	890	900	7.80	28	62.0
		0.37	520	25	890	900	7.80	28	60.4
		0.37	520	25	890	900	7.80	28	60.0
		0.37	520	25	890	900	7.80	28	62.1
		0.37	520	25	890	900	7.80	28	61.4
		0.37	520	47	890	900	7.80	28	62.8
		0.37	520	47	890	900	7.80	28	62.0
		0.37	520	47	890	900	7.80	28	61.6
		0.37	520	47	890	900	7.80	28	61.8
		0.37	520	47	890	900	7.80	28	62.1
		0.37	520	68	890	900	7.80	28	65.8
		0.37	520	68	890	900	7.80	28	66.2
		0.37	520	68	890	900	7.80	28	66.8
		0.37	520	68	890	900	7.80	28	66.4
		0.37	520	68	890	900	7.80	28	66.2
		0.37	520	87	890	900	7.80	28	70.0
		0.37	520	87	890	900	7.80	28	70.4
		0.37	520	87	890	900	7.80	28	70.2
		0.37	520	87	890	900	7.80	28	69.8
		0.37	520	87	890	900	7.80	28	70.1
		0.37	520	104	890	900	7.80	28	80.2
		0.37	520	104	890	900	7.80	28	79.8
		0.37	520	104	890	900	7.80	28	79.0
		0.37	520	104	890	900	7.80	28	78.4
		0.37	520	104	890	900	7.80	28	78.6
		0.37	520	120	890	900	7.80	28	80.2
		0.37	520	120	890	900	7.80	28	79.8
		0.37	520	120	890	900	7.80	28	79.0
		0.37	520	120	890	900	7.80	28	78.4
		0.37	520	120	890	900	7.80	28	78.6
Wongkeo et al. [42]	2014	0.30	600	0	1084	595	7.14	3	76.0
		0.30	600	30	1072	595	7.98	3	73.7
		0.30	600	60	1059	595	8.58	3	78.3
		0.35	514	0	1131	621	8.24	3	63.4
		0.35	515	26	1120	621	7.71	3	65.5
		0.35	515	26	1120	621	8.24	3	63.4
		0.35	514	51	1110	621	9.00	3	70.8
		0.40	450	0	1166	640	8.10	3	56.8
		0.40	451	23	1157	640	8.57	3	55.6
		0.40	450	45	1147	640	9.45	3	59.8
		0.30	600	0	1084	595	7.14	7	79.3
		0.30	600	30	1072	595	7.98	7	81.6
		0.30	600	60	1059	595	8.58	7	84.5
		0.35	514	0	1131	621	8.24	7	75.2
		0.35	515	26	1120	621	8.24	7	77.6
		0.35	514	51	1110	621	9.00	7	81.2
		0.40	450	0	1166	640	8.10	7	65.6
		0.40	451	23	1157	640	8.57	7	65.8
		0.30	600	0	1084	595	7.14	28	84.0
		0.30	600	30	1072	595	7.98	28	95.3

Author	Year	Ratio W/B	Binder	Silica fume	Fine aggregate	Coarse aggregate	Superplasticizer (SP)	Age (day)	Compressive strength (MPa)
		0.30	600	60	1059	595	8.58	28	100.5
		0.35	514	0	1131	621	8.24	28	83.0
		0.35	515	26	1120	621	8.24	28	85.3
		0.35	514	51	1110	621	9.00	28	91.6
		0.40	450	0	1166	640	8.10	28	72.4
		0.40	451	23	1157	640	8.57	28	75.3
		0.40	450	45	1147	640	9.45	28	79.0
		0.30	600	0	1084	595	7.14	90	88.3
		0.30	600	30	1072	595	7.98	90	99.0
		0.30	600	60	1059	595	8.58	90	106.6
		0.35	514	0	1131	621	8.24	90	85.4
		0.35	515	26	1120	621	8.24	90	90.9
		0.35	514	51	1110	621	9.00	90	100.4
		0.40	450	0	1166	640	8.10	90	80.4
		0.40	451	23	1157	640	8.57	90	82.4
		0.40	450	45	1147	640	9.45	90	86.1
Abib [43]	2004	0.38	500	0	794	725	15.00	7	34.0
		0.40	525	25	794	725	15.00	7	36.0
		0.40	525	25	794	725	15.00	7	36.0
		0.36	525	25	794	725	15.00	7	40.7
		0.32	525	25	794	725	15.00	7	42.5
		0.36	525	25	794	725	15.00	7	40.7
		0.36	525	25	794	725	10.00	7	43.5
		0.36	525	25	794	725	5.00	7	40.0
		0.40	500	0	794	725	7.50	3	28.3
		0.40	500	0	794	725	7.50	7	35.8
		0.40	500	0	794	725	7.50	14	43.0
		0.40	500	0	794	725	7.50	28	45.0
		0.40	500	0	794	725	7.50	90	49.5
		0.36	525	25	794	725	10.00	3	32.8
		0.36	525	25	794	725	10.00	7	39.3
		0.36	525	25	794	725	10.00	14	48.5
		0.36	525	25	794	725	10.00	28	56.3
		0.36	525	25	794	725	10.00	90	60.3
Güneyisi et al. [44]	2010	0.32	550	0	728	935	8.43	28	80.9
		0.32	550	28	724	930	9.56	28	80.4
		0.32	550	55	720	925	10.67	28	85.7
		0.32	550	83	716	920	12.00	28	84.4
		0.32	450	23	823	865	4.88	28	60.7
		0.32	450	45	819	861	5.20	28	58.5
		0.32	450	68	816	858	7.76	28	71.1
		0.32	550	28	724	930	9.56	90	91.1
		0.32	550	55	720	925	10.67	90	99.2
		0.32	550	83	716	920	12.00	90	96.7
		0.32	450	23	823	865	4.88	90	71.2
		0.32	450	45	819	861	5.20	90	76.1
		0.32	450	68	816	858	7.76	90	74.8
Güneyisi et al. [45]	2015	0.35	550	0	688	688	5.50	28	47.8
		0.35	550	28	684	684	6.40	28	53.0
		0.35	550	55	680	680	6.40	28	54.0
		0.35	550	0	688	688	5.50	56	52.0
		0.35	550	55	680	680	6.40	56	55.5
		0.35	550	55	680	680	6.40	56	58.5
Güneyisi et al. [46]	2012	0.35	550	28	684	684	6.40	28	53.0
		0.35	550	55	680	680	6.40	28	54.0
Gesoglu et al. [47]	2009	0.44	451	23	823	865	4.90	28	71.2
		0.44	450	45	819	861	5.20	28	76.1
Gesoglu and Ozbay [48]	2007	0.32	550	0	728	935	8.53	28	80.9
		0.32	550	28	724	930	9.56	28	80.3
		0.32	550	55	720	925	10.67	28	85.6
		0.32	550	83	716	920	12.00	28	84.4

Author	Year	Ratio W/B	Binder	Silica fume	Fine aggregate	Coarse aggregate	Superplaciticizer (SP)	Age (day)	Compressive strength (MPa)
Abdelgader et al. [49]	2014	0.38	450	0	918	918	8.10	7	30.4
		0.40	450	0	903	903	6.75	7	24.0
		0.45	450	0	873	873	3.60	7	32.5
		0.38	450	23	925	925	7.70	7	28.5
		0.40	450	23	911	911	6.41	7	33.0
		0.42	450	23	897	897	3.42	7	33.5
		0.45	450	23	882	882	3.42	7	29.5
		0.38	450	45	933	933	8.10	7	21.5
		0.40	450	45	920	920	6.89	7	28.0
		0.42	450	45	906	906	4.05	7	30.5
		0.45	450	45	893	893	4.05	7	26.0
		0.38	450	68	939	939	7.65	7	22.0
		0.40	450	68	927	927	6.50	7	29.0
		0.42	450	68	914	914	3.83	7	33.0
		0.45	450	68	901	901	3.83	7	27.5
		0.38	450	23	925	925	7.70	28	45.0
		0.38	450	0	918	918	8.10	28	43.0
		0.40	450	0	903	903	6.75	28	39.0
		0.42	450	0	888	888	3.60	28	40.5
		0.45	450	0	873	873	3.60	28	41.0
		0.40	450	23	911	911	6.41	28	44.5
		0.42	450	23	897	897	3.42	28	46.0
		0.45	450	23	882	882	3.42	28	44.0
		0.38	450	45	933	933	8.10	28	42.0
		0.40	450	45	920	920	6.89	28	49.5
		0.42	450	45	906	906	4.05	28	50.5
		0.45	450	45	893	893	4.05	28	46.5
		0.40	450	0	903	903	6.75	90	52.0
		0.42	450	0	888	888	3.60	90	54.0
		0.45	450	0	873	873	3.60	90	49.5
		0.38	450	23	925	925	7.70	90	56.5
		0.40	450	23	911	911	6.41	90	55.0
		0.45	450	23	882	882	3.42	90	52.0
		0.38	450	45	933	933	8.10	90	59.0
		0.40	450	45	920	920	6.89	90	56.0
		0.42	450	45	906	906	4.05	90	57.5
		0.45	450	45	893	893	4.05	90	54.5
		0.38	450	68	939	939	7.65	90	64.0
		0.40	450	68	927	927	6.50	90	62.5
		0.45	450	68	901	901	3.83	90	60.0
Ahari et al. [4]	(2015)	0.44	455	0	883	783	5.75	7	39.0
		0.44	455	18	880	778	6.70	7	40.6
		0.44	455	36	875	774	7.50	7	34.5
		0.44	455	55	870	771	8.00	7	35.5
		0.44	455	18	800	778	6.70	28	53.7
		0.44	455	36	875	774	7.50	28	64.0
		0.44	455	55	870	771	8.00	28	64.0
		0.44	455	0	883	783	5.75	90	51.5
		0.44	455	18	800	778	6.70	90	58.8
		0.44	455	36	875	774	7.50	90	64.6
		0.44	455	55	870	771	8.00	90	66.8
Behfarnia,and Farshadfar, [50]	2013	0.38	444	0	1010	777	5.33	28	53.8
		0.38	444	22	1002	777	5.33	28	63.0
		0.38	444	44	994	777	6.66	28	63.8
		0.38	444	66	986	777	6.66	28	72.1
		0.38	444	0	1010	777	5.33	90	57.0
		0.38	444	22	1002	777	5.33	90	68.0
		0.38	444	44	994	777	6.66	90	67.0
		0.38	444	66	986	777	6.66	90	71.5
		0.38	444	0	1010	777	5.33	180	59.0
		0.38	444	22	1002	777	5.33	180	71.8
		0.38	444	44	994	777	6.66	180	75.8

Author	Year	Ratio W/B	Binder	Silica fume	Fine aggregate	Coarse aggregate	Superplasticizer (SP)	Age (day)	Compressive strength (MPa)
		0.38	444	66	986	777	6.66	180	72.2
		0.38	444	0	1010	777	5.33	28	63.3
		0.38	444	22	1002	777	5.33	270	71.5
		0.38	444	44	994	777	6.66	270	73.8
		0.38	444	66	986	777	6.66	270	81.5
Bingöl,.and Tohumcu, I [7]	2013	0.35	500	0	967	694	8.00	3	61.5
		0.35	500	0	967	694	8.00	7	75.0
		0.35	500	75	948	681	10.00	7	79.0
		0.35	500	0	967	694	8.00	28	78.5
		0.35	500	25	958	687	8.00	28	78.5
		0.35	500	50	954	685	9.00	28	82.5
		0.35	500	75	948	681	10.00	28	87.0
Hassana et al. [51]	2012	0.40	450	50	921	891	5.83	28	41.3
		0.40	450	36	923	893	5.40	28	45.9
		0.40	450	23	926	896	5.15	28	41.9
		0.40	450	14	927	898	4.55	28	37.9
Sabet et al. [52]	2013	0.32	500	100	935	656	12.00	3	37.0
		0.32	500	50	959	656	9.50	28	75.0
		0.32	500	100	935	656	12.00	28	79.5
		0.32	500	50	959	656	9.50	90	73.0
		0.32	500	100	935	656	12.00	90	79.5
		0.32	500	50	959	656	9.50	180	79.5
		0.32	500	100	935	656	12.00	180	87.0
R'mili et al. [53]	2009	0.40	550	50	790	732	6.08	3	30.0
		0.38	440	40	906	839	5.07	3	24.0
		0.42	495	45	849	786	5.57	3	26.0
		0.37	550	50	791	733	6.08	3	30.3
		0.51	359	9	1002	927	2.16	7	24.0
		0.49	368	18	988	915	3.52	7	28.0
		0.45	385	35	964	892	4.56	7	31.5
		0.43	440	40	906	839	5.07	7	33.0
		0.41	495	45	849	786	5.57	7	36.0
		0.49	368	18	988	915	3.52	28	42.5
		0.45	385	35	964	892	4.56	28	48.5
		0.43	440	40	906	839	5.07	28	50.0
		0.41	495	45	849	786	5.57	28	55.5
		0.40	550	50	790	732	6.08	28	60.3
		0.42	495	45	849	786	5.57	28	52.5
		0.37	550	50	791	733	6.08	28	61.0
Asteris and Kolovos [54]	2017	0.33	600	30	900	750	12.00	28	80.4
		0.32	600	60	900	750	12.00	28	79.2
		0.35	500	150	900	600	7.35	28	48.9
		0.35	500	200	900	600	6.21	28	42.2
		0.35	500	250	900	600	5.00	28	35.1
		0.44	451	23	823	865	4.90	28	71.2
		0.44	450	45	819	861	5.20	28	76.1
Safiuddin et al. [55]	2018	0.39	481	48	959	784	7.21	3	63.4
		0.45	421	42	992	812	4.21	3	45.5
		0.39	481	48	959	784	7.21	7	74.5
Vivek et al. [56]	2017	0.40	600	0	810	660	13.80	7	35.0
		0.40	600	30	810	660	13.11	7	34.0
		0.40	600	60	810	660	12.42	7	32.0
		0.40	600	90	810	660	11.73	7	31.0
		0.40	600	0	810	660	13.80	28	63.0
		0.40	600	30	810	660	13.11	28	60.1
		0.40	600	60	810	660	12.42	28	58.1
		0.40	600	90	810	660	11.73	28	55.3
		0.40	600	120	810	660	11.04	28	51.4
		0.40	600	150	810	660	10.35	28	45.1
Khodabakhshian et al. [57]	2018	0.45	400	0	793	1000	1.30	7	46.0
		0.45	400	10	791	1000	1.45	7	48.0
		0.45	400	20	788	1000	1.45	7	48.0

Author	Year	Ratio W/B	Binder	Silica fume	Fine aggregate	Coarse aggregate	Superplasticizer (SP)	Age (day)	Compressive strength (MPa)
		0.45	400	10	791	1000	1.45	28	59.0
		0.45	400	20	788	1000	1.45	28	60.0
		0.45	400	40	784	1000	1.60	28	66.0
		0.45	400	0	793	1000	1.30	56	55.0
		0.45	400	10	791	1000	1.45	56	65.0
		0.45	400	20	788	1000	1.45	56	66.0
		0.45	400	40	784	1000	1.60	56	68.0
		0.45	400	0	793	1000	1.30	90	60.0
		0.45	400	10	791	1000	1.45	90	68.0
		0.45	400	20	788	1000	1.45	90	71.0
		0.45	400	40	784	1000	1.60	90	74.0
		0.45	400	0	793	1000	1.30	180	62.0
		0.45	400	10	791	1000	1.45	180	71.0
		0.45	400	20	788	1000	1.45	180	73.0
		0.45	400	40	784	1000	1.60	180	77.0
Turk et al. [58]	2010	0.36	450	23	990	735	8.00	3	36.2
		0.38	450	45	990	735	8.00	3	33.2
		0.40	450	68	990	735	8.00	3	30.9
		0.40	450	90	990	735	8.00	3	31.3
		0.36	450	23	990	735	8.00	7	43.9
		0.38	450	45	990	735	8.00	7	47.0
		0.40	450	68	990	735	8.00	7	40.9
		0.40	450	90	990	735	8.00	7	40.4
		0.36	450	23	990	735	8.00	28	58.0
		0.38	450	45	990	735	8.00	28	62.8
		0.40	450	68	990	735	8.00	28	68.0
		0.40	450	90	990	735	8.00	28	66.4
Karatas et al. [59]	2010	0.36	450	23	932	793	8.00	28	36.5
		0.38	450	45	932	793	8.00	28	44.1
Kennouche et al. [60]	2013	0.42	460	60	827	798	7.20	7	22.0
		0.42	460	60	827	799	6.00	7	25.0
		0.42	460	60	785	798	8.00	7	27.5
		0.42	460	60	827	798	7.20	14	31.0
		0.42	460	60	827	799	6.00	14	41.0
		0.42	460	60	785	798	8.00	14	33.5
		0.42	460	60	827	798	7.20	28	40.0
		0.42	460	60	827	799	6.00	28	43.5
		0.42	460	60	785	798	8.00	28	41.5
Zende, and Khadiranaikar [61]	2019	0.26	575	86	833	700	2.93	7	43.8
		0.24	575	86	833	700	3.42	7	47.2
		0.22	575	86	833	700	3.81	7	51.0
		0.26	575	86	833	700	2.93	28	55.1
		0.24	575	86	833	700	3.42	28	60.0
Gholhaki et al. [62]	2018	0.37	400	40	1069	766	3.45	7	38.0
		0.37	400	80	1062	761	5.37	7	40.0
		0.37	400	0	1085	778	5.75	28	38.0
		0.37	400	40	1069	766	3.45	28	54.0
		0.37	400	80	1062	761	5.37	28	57.5
Faez et al. [63]	2019	0.44	385	35	960	920	2.76	7	21.1
		0.44	385	35	960	920	2.76	28	26.1
		0.44	385	35	960	920	2.76	90	29.3
Choudhary et al. [64]	2020	0.33	550	0	970	722	7.70	7	39.1
		0.33	550	28	970	722	8.25	7	44.1
		0.33	550	28	970	722	8.25	28	58.2
		0.33	550	0	970	722	7.70	90	56.8
		0.33	550	28	970	722	8.25	90	59.9