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RESEARCH PAPER

Performance Evaluation of RBF Networks with Various Variables to Forecast the Properties of SCCs

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ABSTRACT: In the present study, Radial Basis Function (RBF) neural networks are applied to forecast the compressive strength and elastic modulus of Self-Compacting Concrete (SCC). To construct the models, different experimental specimens of diverse kinds of SCC are gathered from the literature. The data used in the networks are classified into two different sets of input parameters. The results revealed that the proposed RBF models can accurately forecast the properties of SCCs with low test error. Furthermore, a comparison between models with two different sets of inputs proves that the selected parameters as input variables, straightly impress the precision of the networks, in the prediction of the intended outputs.

Keywords: Parameters, RBF Artificial Neural Networks, Self-Compacting Concrete, Test MSE.

1. Introduction

In recent years, self-compacting concrete (SCC) as a precious concrete has been widely welcomed in the construction industry. This concrete has a high flowability that can fill formwork without any additional vibration. SCC's unparalleled property gives it remarkable advantages (Siddique, 2011; Mechaymech and Assaad, 2019).

SCC has significant benefits to the construction industry, such as increasing the speed of construction, decreasing the efforts and cost of the placement and improvement in the working conditions. Furthermore, using of this concrete can conduct to a decrease in the noise pollution in the plants, superior working conditions, and producing the concrete productions with great quality (Maarof et al., 2017; Ouchi et al., 2003; Dehwah, 2012).

Like as other concretes, SCC has a lot of significant properties, which are obtained by experimental work. But the experimental work needs to spend a lot of cost, time and effort. For this reason, utilizing a new method to reduce these experiments can be very helpful.

Recently, many researchers have made use of some techniques to forecast concrete properties. Among these techniques, Artificial Neural Networks (ANNs) are extremely famous to have these significant advantages: i) simple to apply, it means, the neural network has the potential to learn

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straightly from examples and; ii) great precision, this network is able to endure rather incorrect or defective tasks, and approximate outcomes (Topçu and Sarıdemir, 2007).

Nazari and Riahi (2012) predicted physical and mechanical properties of high strength concrete containing CuO nanoparticles with ANN and Genetic Programming. To prepare the models, experimental outcomes of 144 examples produced with 16 diverse mixture proportions were used. The data utilized in the feed-forward networks were classified into a collection of 8 inputs. Based upon the obtained result, artificial neural networks are powerful to forecast the flexural strength and the percentage of the water absorption of this concrete. In addition, ANNs can predict the desired outputs of this kind of concrete better than the Genetic Programming.

Onikeku et al. (2019) designed both ANN and Multiple Linear Regression (MLR) models to predict the compressive strength and slump of concrete blending bamboo leaf ash and baggage ash. Three-layer perceptron neural network was used for prediction. The outcome of this study showed that both models are reliable methods to forecast the desired outputs.

Gupta (2013) utilized a back propagation neural network to forecast the compressive strength of concrete. To construct the network, 55 concrete mixtures were gathered from different sources. The ANN model was designed by using five input parameters including; cement, sand, coarse aggregate, water and fineness modulus. The study concluded that the model can forecast the compressive strength of concrete with good correlation coefficient. It was also found that ANN can be a beneficial modeling technique for engineers in the construction industry.

Ghafari et al. (2015) designed two analytical models based on statistical mixture design (SMD) technique and ANN to approximate the performance of Ultra-High Performance of Concrete (UHPC). The networks were trained by using 53 different mixtures. Heat treatment and water storage were considered as curing conditions for specimens. The results showed that the ANN model can predict the slump flow and compressive strength of UHPC with higher precision than the SMD.

Al-Khatib and Al-Martini (2019) predicted the rheology of SCC under hot weather. The input parameters were the mixing time, supplementary cementitious materials and the ambient temperature. In addition, the relative yield stress, slump flow and relative viscosity were selected as output variables. Akaike information criterion and mean absolute percentage error were applied to appraise the networks. The outcomes displayed that the created networks are able to forecast the rheological properties of this concrete.

Li et al. (2011) predicted the workability of SCC with neural network. The data used in the ANN were classified into a format of six inputs, including fly ash, super plasticizer, cement, blast furnace slag, water/binder and sand ratio. The outputs of this concrete were V-test, slump and slump flow. Three models (ANN-1, ANN-2 and ANN-3) with 15, 11 and 5 neurons in the hidden layers were designed. Eventually, a comparison between the predicted and experimental outcomes indicated that ANN-2 had the greatest performance to predict the workability of SCC utilizing concrete ingredients as input variables.

A review of the past studies reveals that in spite of the different work reported on utilizing neural networks, a limited amount of work has been done with the aim of developing SCC by using ANN method. Therefore, the main goals of this investigation are to estimate the potential of RBF ANNs to forecast the compressive strength and elastic modulus of SCC under conditions that:

1) The scattering and diversity of the sources and specimens utilized in this study is high. The results of this study display that even in a complex situation along with the scattering of the specimens, an optimized

RBF neural network will be able to provide the optimal precision.

2) The constructed comprehensive models cover diverse kinds of SCC containing different materials (i.e. SCC with various pozzolans, fibers, recycled materials, and lightweight aggregates). It means, in contrast with some researches, such as (Mlv and Prasenjit, 2019; Prasad Meesaraganda et al., 2019), this study does not focus on just one kind of SCC. The present research clearly illustrates the excellent ability of RBF neural networks to forecast the valuable properties of SCCs.

3) The parameters that are selected as input variables in the RBF neural networks are different. This investigation exhibits the impact of the selected input factors on the performance of the RBF networks in the prediction of the desired outputs.

For these goals, experimental data from various specimens of SCC were collected from literature. These data were used for training and testing the comprehensive models. Two different collections of input parameters were considered for networks. A comparison between the outcomes acquired from the models with different inputs was done and eventually, the forecasted outcomes from the best models were compared with the actual outcomes.

2. Artificial Neural Networks

The main unit of the human brain is neuron that each neuron acts as a numeric processing. Like as the human brain, ANNs consist of many interconnected artificial neurons, which known as processing elements, nodes or units (Barkhordari Bafghi and Entezari Zarch, 2015). The well-organized processing elements working to solve the specific problems (Bhargava, 2019). These elements interact with each other through weighted connections. The nature and the power of the influence between the interconnected processing elements are specified by the weights. There is an input layer where data are presented to the network and an output layer that represents the response of the network to the input (Goh, 1995; Bhargava, 2019). Another layer, which is called hidden layer helps network to prepare nonlinear mapping of the data to forecast the intended output (Ashtiani et al., 2018). An artificial neuron design is shown in Figure 1.

ANN is a computer program that aims at simulating the behavior of the real brain (Shmelova et al., 2019; Kok et al., 2010). The neural network is featured via self-adaptive, self-learning, immense parallelism and extremely non-linear explanation, which can lead to discovering intricate relationships between input and output parameters (Zhang et al., 2010; Demirhan et al., 2007). A design of RBF network, which is utilized in this paper, is shown in Figure 2.

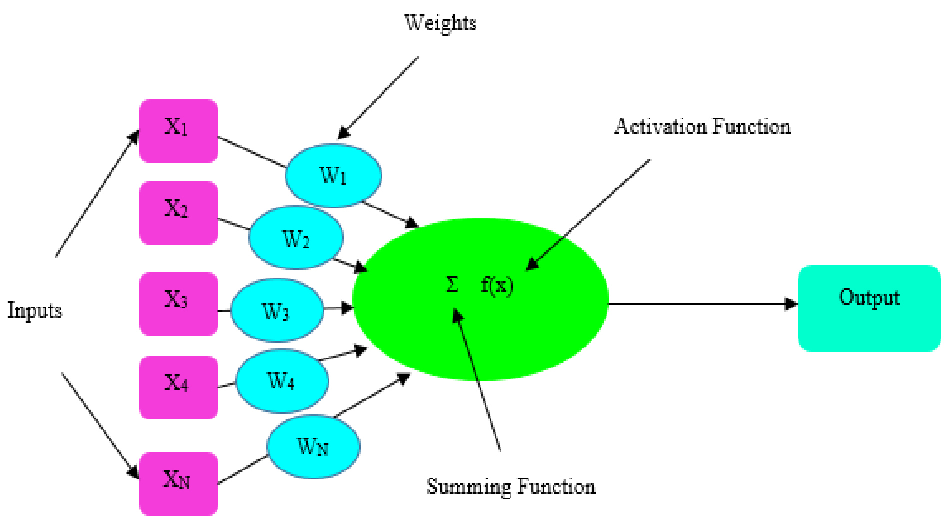


Fig. 1. An artificial neuron design

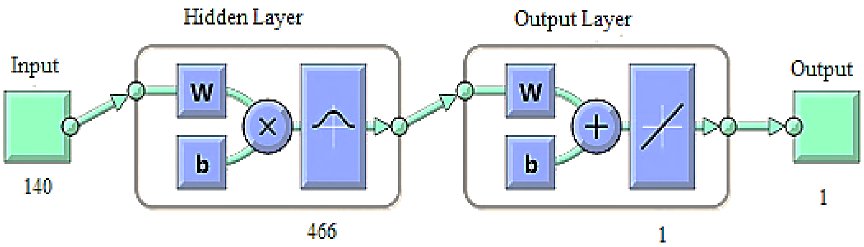


Fig. 2. A schematic of RBF neural network

Among different types of the neural networks, one of the most used ANN models is the radial basis function (RBF) network, which is a kind of feed forward ANN that learns via a supervised training method. This network has a simple structure, fast learning convergence and the strength to estimate any nonlinear function (Bielecki and Wojcik, 2017). They are useful in function estimation, assortment, and modeling of dynamic systems and time series (Tsai and Chuang, 2004). The first time, Broomhead and Lowe (1998) used radial basis functions for the design of the artificial neural networks.

Generally, the architecture of this network includes an input layer, a hidden layer along with a non-linear activation function and a linear output layer (Kopal et al., 2019). The input layer of the ANN gets signals from the outer environment. These signals transfer to the hidden layer. Finally, the hidden layer transfers an output signal to another layer based on a transfer function (Miller, 2011). The network structure is shown in Figure 3.

In Figure 3, X_n, y_m and ϕ_H: are the input, the output and the activation function, respectively. For each hidden layer neuron, the output equation, $\psi_{i(x)}$, which can also be stated as Gaussian function, can be obtained from the below function (Eq. (1)) (Orak Boru et al., 2014):

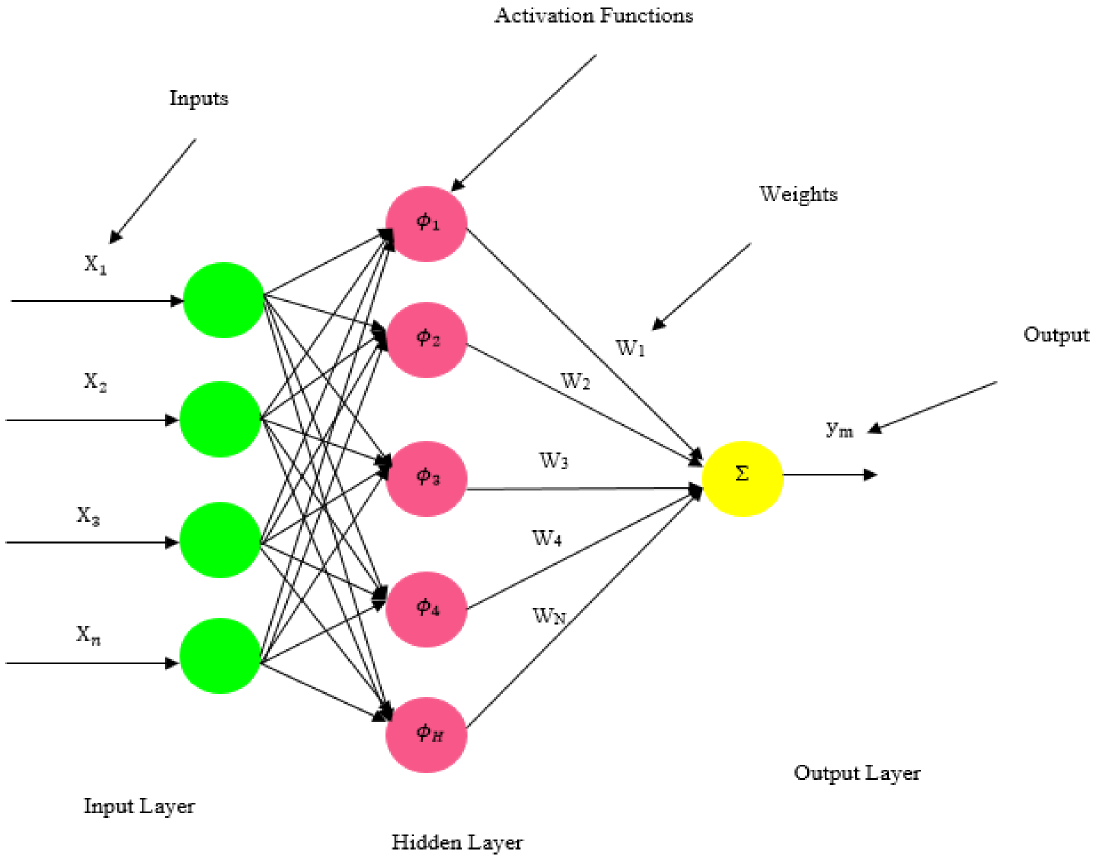


Fig. 3. Architecture of RBF neural network

$$\psi_{i(x)} = \frac{exp(-\sum_{j=1}^{r}[x_j - c_i]^2)}{\sigma_i^2} \quad (1)$$

where; x_j, ci, σ_i and exp: show the inputs of the network, center vector of each hidden layer neuron, spread value and the exponential function, respectively. For each neuron in the output layer, data come from hidden layer that are computed by Eq. (1). For each output neuron, the generalized output equation can be obtained as Eq. (2):

$$y_m = b_m + \sum_{i=1}^{H} w_{im}\, \psi_{i(x)} \quad (2)$$

where H, w_{im}, b_m and m: are the number of hidden layer neurons, the weights, the bias amount and the number of neuron in the output layer, respectively (Orak Boru et al., 2014).

In order to train the network, first, according to training algorithm, the centers of hidden layers are selected via various techniques such as, randomly, k-means clustering and so on. Then, for the output layer, linear functions with w_i values are fitted (Schwenker et al., 2001). For hidden layer, the algorithm calculates the output values through specifying the centers with Eq. (1). After that, the output is estimated by utilizing Eq. (2). Finally, a comparison between the obtained outputs specify the error of the network. The training process of the network continues until the error reaches the desired value, through adding neurons to the ANN and with updating the weights and centers of neurons in each iteration (Xie et al., 2011).

3. Details of the Networks Preparation

3.1. Data Description

To construct RBF models, experimental data from various sources were gathered (Adekunle et al., 2015; Omrane et al., 2017; Ozodabas, 2018; Kamal et al., 2015; Celik, 2015; Alyousef, 2018; Beigi et al., 2013; Krishna and Anil, 2018). For 28-day elastic modulus, 38 samples, and for compressive strength at 7, 28 and 90 days, 275, 549 and 203 samples were utilized, respectively. For all of these mechanical properties, 85 percent of all data were used for training the networks, and 15 percent of remaining data were used for testing ANNs.

At the first time, in order to simulate a real laboratory conditions, a more complete set of key factors affecting the intended outputs, as input variables, were selected for models. These variables were arranged in a format of 140 efficient inputs, including:

- Maximum size of gravel and lightweight aggregates (mm);
- The amounts of sand, gravel, recycled materials, lightweight aggregates, cement, limestone powder, fibers basalt, polyvinyl alcohol (PVA), high toughness poly-propylene (PPHT), carbon and steel), pozzolans (fly ash, basaltic ash, sawdust ash, ground granulated blast furnace slag (GGBFS), metakaolin, silica fume and zeolite.), water, polymer and nano-silica, (Kg/m^3);
- The shapes of gravel, including: fully rounded corner, rounded corner, relatively rounded corner, relatively sharp corner and sharp corner;
- Specific gravity of sand, gravel, pozzolan, lightweight aggregates, recycled materials, cement, fiber, limestone powder, super plasticizer, nano-silica, high water reduction agent (HWRA) and viscosity-modifying agent (VMA), (gr/cm^3);
- Diameter (mm), length (mm), tensile strength (MPa) and the shapes of the fibers, including: fiber with straight end and fiber with hooked end;
- Grading of lightweight aggregates, sand and gravel;
- Water absorption of lightweight aggregates, sand and gravel (%);
- Chemical properties of cement, pozzolan, recycled materials, and limestone powder;
- Temperature operation (°C);
- Solid contents of nano-silica and super plasticizer (%);
- PH of super plasticizer;
- Dosage of viscosity-modifying agent

(VMA), super plasticizer, and high water reduction agent (HWRA), (Kg/m^3);

- Concrete's delivery time (min);
- Curing conditions (wet, dry, sealed).

It is worth mentioning that introducing the different shapes of fiber, sand and also various curing conditions to the ANNs were carried out by devoting constant digits for each parameter according to Table 1.

At the second time, some of the parameters affecting the properties of concrete were ignored. In the other words, first, to take prediction conditions closer to laboratory conditions, the authors selected input parameters more sensitively. But, at the second time, this sensitivity was reduced and they just tried to collect the parameters, which have been selected repeatedly as the input factors among similar investigations in this field. Then, these gathered parameters were classified into a set of 8 inputs, namely: the amounts of sand, gravel and cement, water-to-cement materials ratio, super plasticizer dosages and specific gravity of sand, gravel and cement (Khademi and jamal, 2016; Das et al., 2015; Shah et al., 2018; Rajaram et al., 2018; Yuan et al., 2014). For each network, compressive strength or elastic modulus of SCCs was determined as output parameter.

3.2. Designs of Models

To construct and train the models, the MATLAB Neural Network Toolbox was used. For the structure of the models, one input layer, one hidden layer along with a non-linear RBF activation function that is called Gaussian activation function, and one output layer with a linear activation function namely Purelin were considered. The number of input and output layer neurons are equivalent to the number of input and output parameters (Kazemi Elaki et al., 2016). Therefore, for networks with 8 and 140 input variables, the number of input layer neurons were 8 and 140 with one neuron in the output layer. Furthermore, for this network, the MATLAB software automatically determined the number of hidden layer neurons, similar to the number of data that were considered for network training (i.e. 85 percent of all data for each mechanical property). The number of neurons in each layer and their activation functions are shown in Table 2.

It should be noted that optimizing the spread parameter of RBF ANN is so important and it can directly influence the degree of estimation (Lihui et al., 2008). Therefore, in this study, in order to obtain the optimal spread, which leads to the minimum test error, the spread values of the radial basis function networks have been set between 0.1 and 10^9. This domain was selected by trial and error method.

3.3. Data Normalization

Before training the neural networks, the values of the training and test data were normalized between 0 and 1 by using the following codes in MATLAB software:

Table 1. Introducing the various shapes of fiber, sand and also different curing conditions to the networks

Sand	Fiber	Curing conditions
Fully rounded corner = 0	Fiber with straight end = 0.5	Dry conditions = 0
Rounded corner = 0.25	Fiber with hooked end = 1	Wet conditions = 1
Relatively rounded corner = 0.5		Sealed conditions = 2
Relatively sharp corner = 0.75		
Sharp corner = 1		

Table 2. Characteristics of the designed ANNs

Outputs	Number of neurons in the input layer	Number of neurons in the hidden layer	Number of neurons in the output layer	Activation function in the hidden layer	Activation function in the output layer
7-day Compressive strength	8 or 140	234	1	Gaussian	Purelin
28-day Compressive strength	8 or 140	466	1	Gaussian	Purelin
90-day Compressive strength	8 or 140	173	1	Gaussian	Purelin
28-day Elastic modulus	8 or 140	32	1	Gaussian	Purelin

$$[pn, ps] = mapminmax\ (p, 0, 1) \quad (3)$$

$$[tn, ts] = mapminmax\ (t, 0, 1) \quad (4)$$

where p, t, pn, tn: illustrate the original inputs, the original targets, the normalized inputs, and the normalized targets, respectively. Furthermore, ps and ts: show the minimum and maximum amounts of the original inputs and targets (MATLAB Software, 2013).

3.4. ANN Model Performance

To appraise the outcomes of the models, Mean Square Error (MSE) and the Correlation Coefficient (R) were exerted. These functions are determined as Eqs. (5-6):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_{experimental_{(i)}} - X_{calculated_{(i)}})^2 \quad (5)$$

$$R = [1 - \frac{\sum_{i=1}^{N}(X_{experimental_{(i)}} - X_{calculated_{(i)}})^2}{\sum_{i=1}^{N}(X_{experimental\,(i)} - \overline{X_{experimental}})^2}]^{1/2} \quad (6)$$

where N; $X_{calculated}$, $X_{experimental}$, and $\overline{X_{experimental}}$: are the number of data sets, calculated amount, experimental amount, and average of experimental amounts, respectively (Badrnezhad and Mirza, 2014). The correlation coefficient (R) varies between -1 and +1. It means, this characteristic will be either 1 or –1, when two parameters are in full linear correlation. The correlation coefficient 0 shows that the parameters have no linear correlation with each other (Schober et al., 2018).

4. Results and Discussions

The ANN models developed in this research were used to forecast the compressive strength and elastic modulus of SCCs. To assess the impact of the selected input factors on the network accuracy in the prediction of the intended properties, the data were classified into two sets of 8 and 140 inputs. As mentioned earlier, 85 percent of all samples (chosen randomly) were applied for training the networks and 15 percent of remaining samples were used to test the prediction.

The statistical values of the developed ANN models at different spreads are shown in Tables 3 and 4. The specified column in each table for each output shows that the network at this spread has the minimum test error and consequently the highest accuracy in predicting the desired outputs. It means, at these specified spreads, the predicted outcomes have a very good agreement with the experimental outcomes. For each output, this spread is called the Network's optimal spread. Furthermore, it is worth mentioning that, this network can be made in a very short time and also can be trained much faster than other kinds of ANNs.

In Table 5, the outcomes of RBF networks with two different sets of inputs were compared with each other. As it can be seen, the created RBF networks with 140 inputs have lower test error and consequently a greater accuracy than networks with 8 inputs in forecasting the intended outputs. In fact, by deleting some of the input factors, a relatively large variation has been created in the forecasted outcomes.

In addition, for both elastic modulus and compressive strength, RBF networks with 140 inputs compared to ones with 8, have 85.65 (for 28-day elastic modulus) and, 64.48, 63.25, and 83.53 (for 7, 28 and 90-day compressive strength, respectively) percent improvement regarding their test MSE. This demonstrates that by the more simulation of the forecasted conditions to the laboratory conditions, through selecting a more perfect set of key variables affecting the intended properties, as input factors, the network performance can significantly be improved. For this reason, in this investigation, owing to have the minimum test MSE and the highest correlation coefficients, the optimized models with 140 variables are selected as the best models.

Table 3. Statistical values of the developed ANN models with 8 inputs

	Spreads	**0.1**	**1**	**10**	**10^2**	**10^3**	**10^4**	**10^5**	**10^6**	**10^7**	**10^8**	**10^9**
FC7[*1]	Test MSE	8.89e+11	1.18e+06	73.39	**47.17**	66.02	78.55	78.56	78.56	149.07	149.81	149.82
	Train MSE	3.18	3.23	11.53	**41.41**	61.4	76.49	76.49	76.61	140.28	144.35	144.35
	Test R	-0.01	-0.35	0.75	**0.82**	0.73	0.67	0.67	0.67	0.17	-6.31e-30	-6.31e-30
	Train R	0.98	0.98	0.95	**0.84**	0.77	0.69	0.69	0.69	0.21	-8.66e-29	-8.66e-29
FC28[*2]	Test MSE	1.83e+13	3.26e+05	**64.42**	97.37	186.95	210.76	210.76	210.78	299.29	301.77	301.77
	Train MSE	13.29	14.04	**33.31**	100.01	188.01	217.11	217.11	217.16	333.87	337.61	337.61
	Test R	0.27	0.23	**0.89**	0.82	0.61	0.55	0.55	0.55	0.22	-7.16e-28	-7.16e-28
	Train R	0.98	0.97	**0.94**	0.83	0.66	0.59	0.59	0.59	0.23	8.74e-27	8.74e-27
FC90[*3]	Test MSE	3.33e+09	1.27e+10	1.45e+03	**92.7**	113	180.68	180.68	180.88	309.28	439.84	439.84
	Train MSE	47.03	47.03	54.83	**54.9**	70.21	173.27	173.27	173.29	296.79	442.13	442.14
	Test R	0.24	-0.15	0.69	**0.88**	0.86	0.76	0.76	0.76	0.54	-0.2	0
	Train R	0.94	0.94	0.93	**0.92**	0.91	0.77	0.77	0.77	0.57	-0.27	-1.70e-26
ES28[*4]	Test MSE	783.82	**7.25**	9.73	9.22	10.62	9.27	9.27	9.22	11.44	82.02	82.02
	Train MSE	1.04	**1.03**	1.03	1.04	1.20	2.81	2.81	2.80	5.71	38.84	38.84
	Test R	0.62	**0.96**	0.95	0.96	0.95	0.96	0.96	0.96	0.95	-2.01e-29	-2.01e-29
	Train R	0.98	**0.98**	0.98	0.98	0.98	0.96	0.96	0.96	0.92	-1.35e-28	-1.35e-28

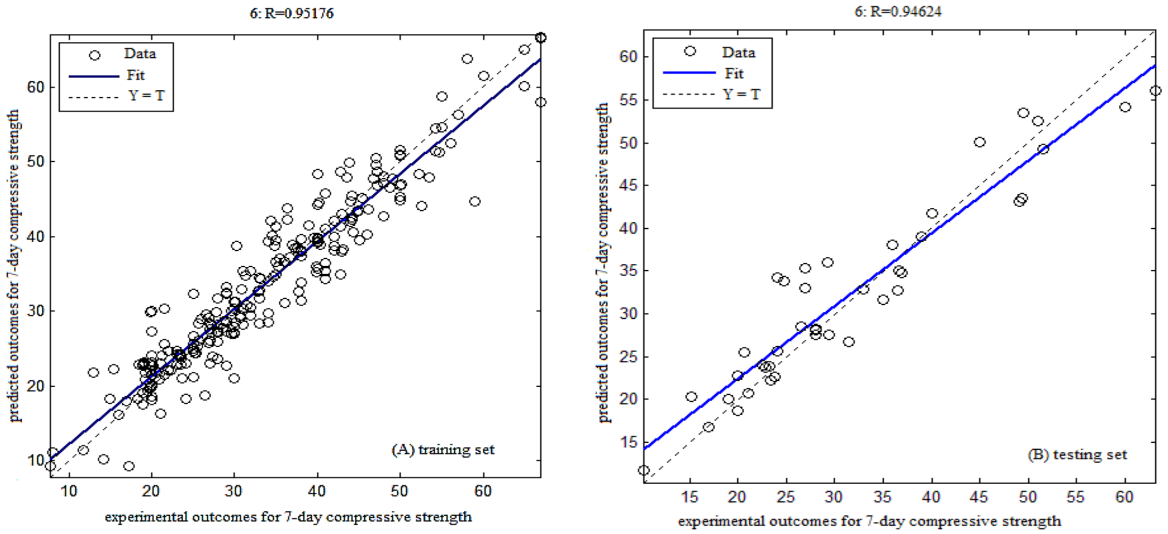
*[1]: 7-day compressive strength; *[2]: 28-day compressive strength; *[3]: 90-day compressive strength; *[4]: 28-day elastic modulus

Table 4. Statistical values of the developed ANN models with 140 inputs

	Spreads	**0.1**	**1**	**10**	**10^2**	**10^3**	**10^4**	**10^5**	**10^6**	**10^7**	**10^8**	**10^9**
FC7	Test MSE	1.33e+13	1.54e+15	7.80e+04	272.92	17.11	**16.59**	17.62	18.34	85.08	154.13	154.13
	Train MSE	9.05e-12	0.02	0.06	0.77	5.19	**13.52**	13.59	15.61	70.27	143.61	143.60
	Test R	0.20	0.16	0.03	0.58	0.94	**0.94**	0.94	0.93	0.66	-2.40e-29	-2.40e-29
	Train R	1	0.99	0.99	0.99	0.98	**0.95**	0.95	0.94	0.71	-1.35e-28	-1.35e-28
FC28	Test MSE	4.26e+09	8.91e+06	5.90e+04	450.96	**23.67**	36.20	34.54	36.88	152.55	348.49	348.87
	Train MSE	8.69e-04	8.69e-04	0.59	3.79	**11.91**	32.40	33.15	35.81	139.02	329.52	329.31
	Test R	0.10	0.03	0.05	0.69	**0.96**	0.94	0.94	0.94	0.74	-0.23	-8.61e-29
	Train R	1	1	0.99	0.99	**0.98**	0.94	0.94	0.94	0.76	-0.22	-1.05e-26
FC90	Test MSE	1.93e+05	6.26e+12	1.65e+06	650.87	**15.26**	52.38	52.66	52.57	158.77	298.75	298.75
	Train MSE	1.66e-24	8.63e-11	0.003	3.05	**7.35**	38.66	38.73	39.92	139.34	466.66	466.67
	Test R	-0.29	0.28	0.32	0.54	**0.97**	0.90	0.91	0.91	0.69	-2.01e-28	-2.03e-28
	Train R	1	1	1	0.99	**0.99**	0.95	0.95	0.95	0.83	6.19e-27	6.19e-27
ES28	Test MSE	39.81	3.33	3.22	1.37	3.82	**1.04**	1.23	2.42	1.08	13.92	39.95
	Train MSE	9.42e-29	3.26e-26	5.21e-18	9.12e-10	0.01	**1.20**	1.21	1.85	2.47	15.30	46.20
	Test R	0.77	0.97	0.98	0.98	0.98	**0.99**	0.99	0.97	0.99	0.84	0
	Train R	1	1	1	1	0.99	**0.98**	0.98	0.97	0.97	0.83	9.85e-29

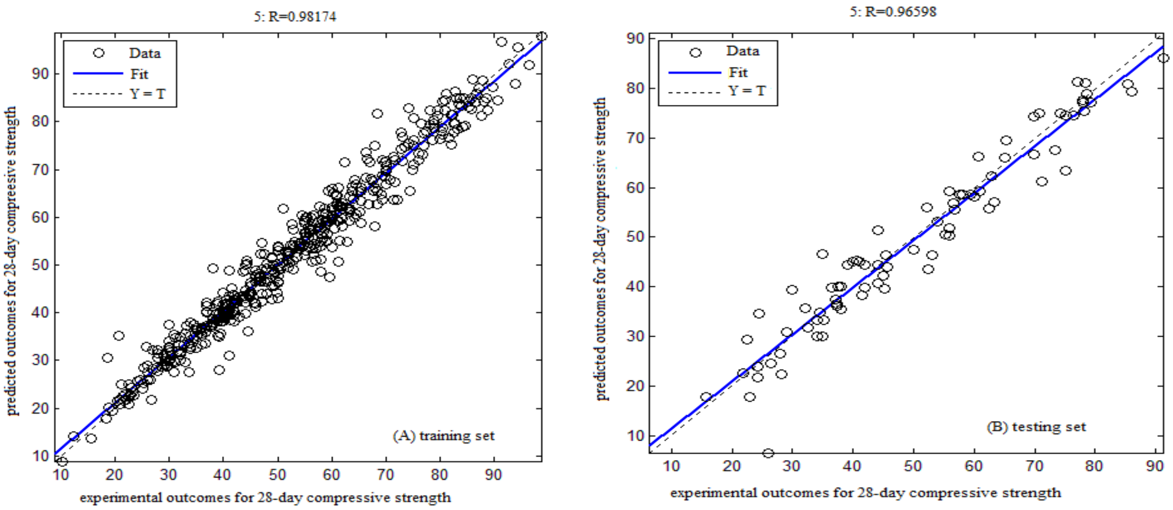
The performance of training and testing data sets of the best models of RBF neural networks with 140 input variables is displayed in Figures 4-7. Based on these figures, the values of R in training and test sets, were obtained (0.95, 0.94, 0.98, 0.96, 0.99, 0.97) for 7, 28 and 90-day compressive strength, and (0.98, 0.99) for 28-day elastic modulus, respectively. As mentioned earlier, the correlation coefficient (R) determines the power of the relationship between the parameters. The R value close to one shows an excellent agreement between two parameters.

Therefore, pursuant to these figures, for both compressive strength and elastic modulus, the values obtained through the training and testing of RBF models are in a good correlation with actual values. It indicates the optimized networks successfully learned the relationship between the selected input and outputs. In the other words, the obtained R values proves that there is a great fitness between the forecasted and experimental outcomes at all the operating conditions considered in this study. Therefore, without requirement to do any experiment, a finely-trained and tested neural network, as a valuable tool, is able to forecast the various properties of SCCs, along with a notable reduction in time and cost.



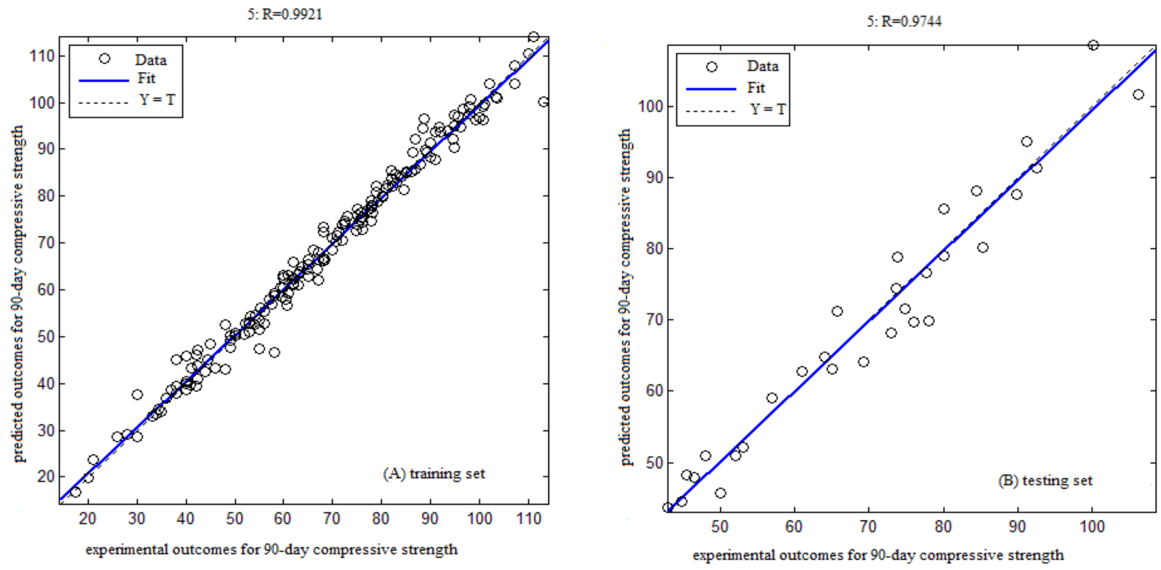
(a) **(b)**

Fig. 4. Predicted outcomes vs. experimental outcomes for 7-day compressive strength: a) Training set and; b) Testing set



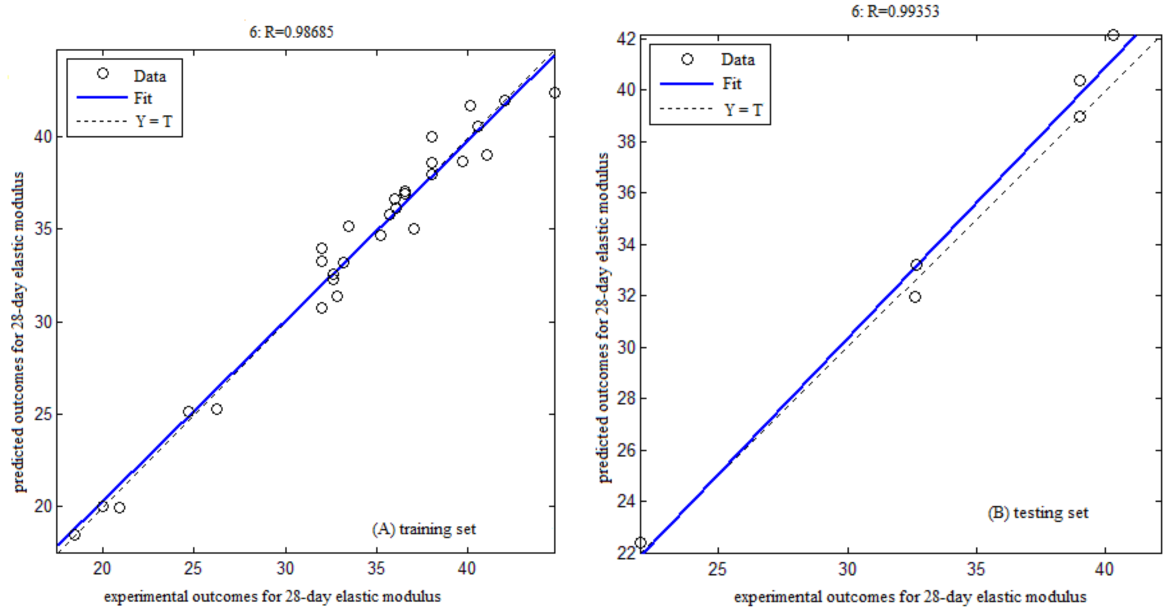
(a) **(b)**

Fig. 5. Predicted outcomes vs. experimental outcomes for 28-day compressive strength: a) Training set and; b) Testing set



(a) **(b)**

Fig. 6. Predicted outcomes vs. experimental outcomes for 90-day compressive strength: a) Training set; b) Testing set



(a) **(b)**

Fig. 7. Predicted outcomes vs. experimental outcomes for 28-day elastic modulus: a) Training set and; b) Testing set

Table 5. Comparison between the outcomes of the optimized models with 8 and 140 inputs

Outputs	Number of inputs	Optimum spreads	Test MSE	Train MSE	Test R	Train R	Percentage of improvement in test MSE
FC7	8	10^2	47.17	41.41	0.82	0.84	64.48
	140*	$\mathbf{10^4}$	**16.59**	**13.52**	**0.94**	**0.95**	
FC28	8	10	64.42	33.31	0.89	0.94	63.25
	140*	$\mathbf{10^3}$	**23.67**	**11.91**	**0.96**	**0.98**	
FC90	8	10^2	92.70	59.40	0.88	0.92	83.53
	140*	$\mathbf{10^3}$	**15.26**	**7.35**	**0.97**	**0.99**	
ES28	8	1	7.25	1.03	0.96	0.98	85.65
	140*	$\mathbf{10^4}$	**1.04**	**1.20**	**0.99**	**0.98**	

*: The best models

Furthermore, a comparison between the actual and predicted outcomes of the best models with 140 variables are illustrated in Figures 8-11. As can be observed in these figures, the predicted outcomes of the RBF networks have an excellent conformity with the actual results. The performance and the prediction accuracy of these optimized networks is suitable, and for this reason the outputs of the models are close to the actual values. This case proves that the designed RBF networks, which contain a more perfect set of key factors affecting the desired outputs, are fully powerful to forecast all of the properties of this concrete. In fact, RBF networks, as a reliable tool, can predict the properties of SCCs in a quite short period of time with low error values.

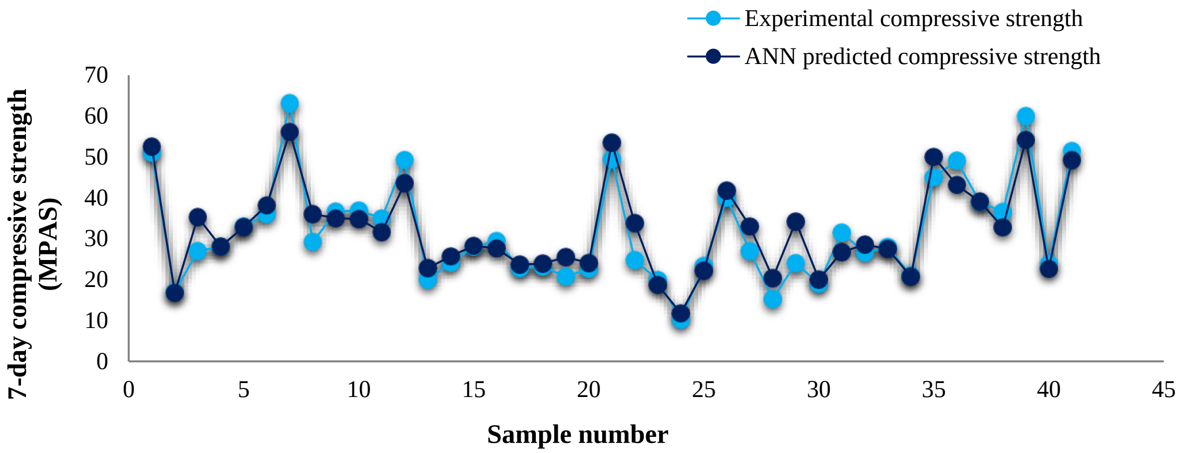


Fig. 8. Comparison between the predicted and experimental values of 7-day compressive strength

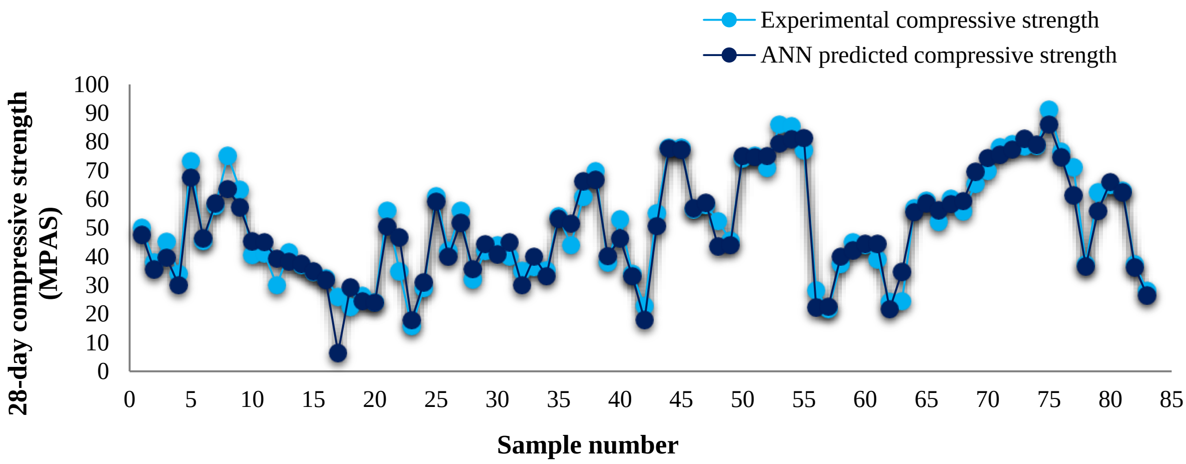


Fig. 9. Comparison between the predicted and experimental values of 28-day compressive strength

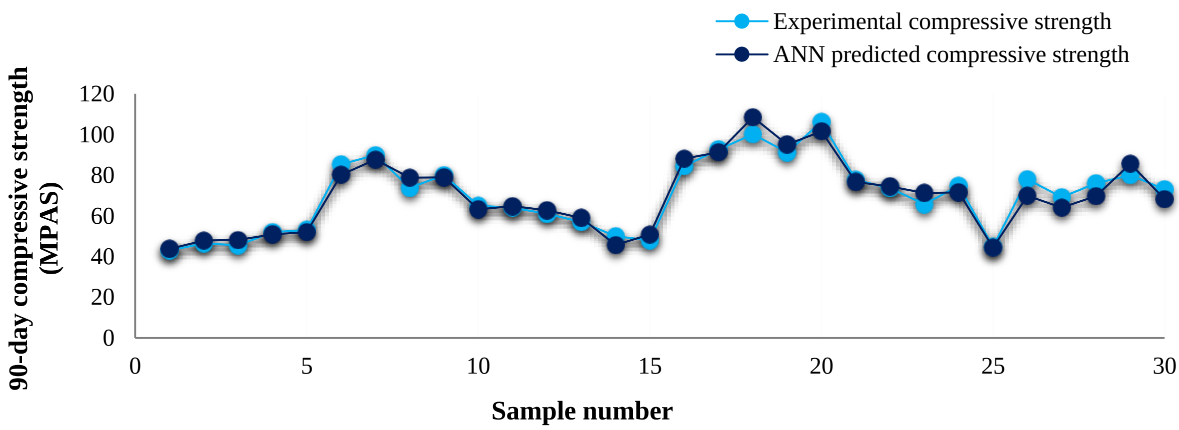


Fig. 10. Comparison between the predicted and experimental values of 90-day compressive strength

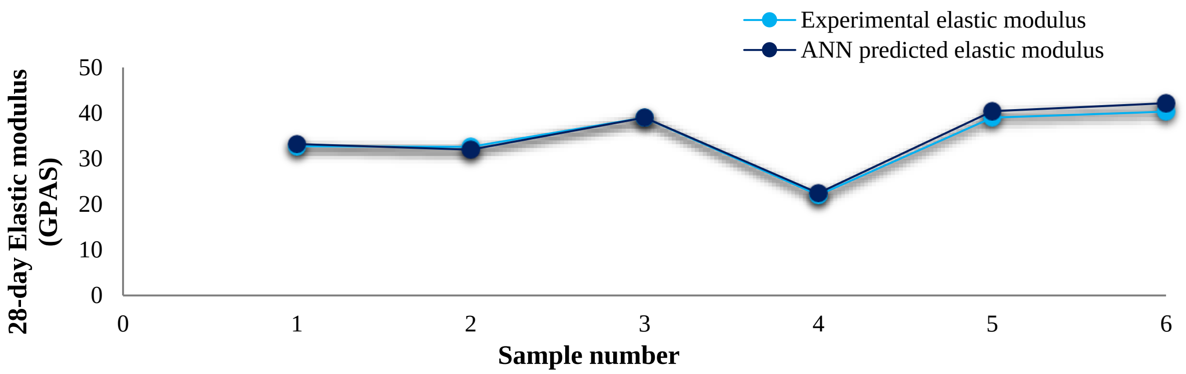


Fig. 11. Comparison between the predicted and experimental values of 28-day elastic modulus

5. Conclusions

Self-compacting concrete is a very valuable type of concrete that has a lot of significant benefits in the construction industry. Similar to other concretes, the valuable mechanical properties of this concrete, such as compressive strength and elastic modulus, are obtained in the laboratory, which is time-consuming and costly. The remarkable aim of the current paper is to design and develop comprehensive models of RBF neural networks to forecast the compressive strength and elastic modulus of self-compacting concretes. Experimental data from the different concrete mix-designs of SCC were collected from various sources to design the models. The data utilized in RBF networks were classified into two different sets of input parameters. The spread values of the constructed networks were set between 0.1 and 10^9 to obtain the optimal spread.

Based on the present research, the following conclusions are drawn:

1. The RBF artificial neural network, as a smart tool, has a high potential to forecast the properties of SCCs. It is clearly seen from this study that, in spite of the fact that the dispersal of the utilized data can cause a decrease in the prediction precision of the models, the optimized models of RBF networks can estimate the properties of different kinds of self-compacting concretes with a fairly good precision.
2. The RBF neural network can be made and trained much faster than other types of neural networks. This network is able to be optimized in a very short time. All of the designed networks were optimized through finding an optimum spread value for each output. The great conformity between the forecasted and experimental outcomes proves that the optimized RBF neural networks can learn well the relationship between the selected input and output parameters.
3. In comparison with experimental work, which needs to spend a lot of time, cost and material, radial basis function neural networks can predict the essential properties of this useful concrete without performing any experiments along with a high accuracy. In the other words, these developed networks will save time, decrease waste material and reduce the design expense in predicting the desired outputs of SSCs.
4. For all of the intended properties, developed RBF neural networks with 140 variables, have a better performance than networks with 8 variables. It reveals that whatever the conditions of predicting the neural networks get closer to laboratory conditions, via using a more perfect set of input variables affecting the intended outputs, the RBF ANNs can forecast the outputs more correctly. Therefore, if input variables are selected more sensitively, this selection straightly influences the network errors and consequently, the created networks present a highly satisfying performance to forecast the outputs.

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