Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Predicting The Strength Properties of Self Healing Concrete Using Artificial Neural Network

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https://doi.org/10.22115/SCCE.2022.349792.1478

ARTICLE INFO

Article history:
Received: 30 June 2022
Revised: 17 December 2022
Accepted: 26 December 2022

Keywords:
Rootmean square error;
Artificial neural network;
SHC;
Crystalline admixture;
Mineral admixture.

ABSTRACT

An extensive simulation program is used in this study to discover the best ANN model for predicting the compressive strength of concrete with respect to the percentage of mineral admixture and percentage of crystalline admixture. To accomplish this, an experimental database of 100 samples is compiled from the literature and utilized to find the best ANN architecture. The main aim of this paper was to predict the strength properties of self-healing concrete (SHC) with crystalline admixture and different mineral admixtures using an artificial neural network (ANN). The samples, 100 in Number, with different mixes, were analyzed after 28 days of curing of the samples. ANN was fed with the experimental data containing four input parameters: mineral admixture (MA), percentage of mineral admixture (PMA), Percentage of crystalline admixture (PCA), and type of exposure (TE). Correspondingly, strength (Fc) was the output parameter. The experimental data showed a good correlation with the values predicted by ANN. In conclusion, ANN could be used to accurately evaluate SHC strength characteristics.

How to cite this article: Theja AR, Reddy MS, Jindal BB, Sashidhar C. Predicting the strength properties of self healing concrete using artificial neural network. J Soft Comput Civ Eng 2023;7(1):56–71. https://doi.org/10.22115/scce.2022.349792.1478

1. Introduction

Concrete is the most extensively used building material in the world. Despite being cost-effective and capable of supporting relatively large compressive loads, concrete is subject to micro-cracks, which may compromise the lifespan of civil infrastructure and result in multibillion-dollar losses due to early deterioration. Several causes may contribute to creating cracks in a concrete matrix, including mechanical stress, restricted shrinkage or thermal deformation, differential settlement, inadequate building techniques, and shoddy workmanship. Therefore, hazardous chemicals such as chloride ions, sulphates, and carbon dioxide may readily enter the concrete matrix, resulting in corrosion of the reinforcing steel and concrete degradation. In addition, typical concrete repair and rehabilitation treatments are generally ineffective and time-consuming. According to Franklin [1], the cost of maintenance and rehabilitation of existing civil infrastructure has surpassed the cost of creating new infrastructure, particularly in industrialized nations. A recent assessment by the American Society of Civil Engineers (ASCE) assigned a grade of D+ to the present state of the American national infrastructure (equivalent to poor condition). It is also anticipated that $3.6 trillion will be required by 2020 to restore the aging infrastructure. In fact, deteriorating civic infrastructure depletes financial resources and has social and environmental consequences.

In recent years, research on the self-healing capabilities of concrete has acquired exponential importance. The concept of bio-mimicry and the natural healing process presented the stimulation [2–4]. For example, when cuts, scrapes, or scratches harm human or animal skin, it may self-heal naturally. Although it is challenging to duplicate this same biological healing process in concrete, several experiments have shown that a Portland cement concrete matrix may mend itself inherently.

Developing a cement mixture including crystalline admixtures [5–8] and supplemental cementitious materials, which will replace the present mixes to improve the durability, quality of the structure, and construction costs, is a significant answer to the concerns mentioned above. Concrete is often susceptible to cracking. These fractures might develop at any point throughout their existence. The formation of polymers due to physical and chemical bonding may be attributed to the interaction of polymers with monomers and chains. Thermoplastic polymers are essential because they may be altered after being subjected to external temperature and transforming into a liquid state. This interaction between the polymer and the concrete gives fracture healing effectiveness.

The fissures in the self-healing concrete are capable of sealing themselves. It works by hydrating previously unhydrated cementitious material and calcites, expanding concrete in fracture sides, closing cracks with loose concrete, and so on. When analyzing fracture widths, self-healing must be taken into account. Different studies have suggested various fracture widths ranging from 5 to 300 μm. It has been observed that the proper crack width poses a substantial obstacle to complete fracture healing. Because regular concrete may become brittle when subjected to mechanical stress. These little fissures are of tremendous importance and are regarded as essential elements in the concrete's ability to self-heal.

2. Research significance

Analysis of the relationship between strength and its affecting elements might aid in identifying SHC strength characteristics. Studies reveal that the strength characteristics of SHC largely depend on the type, nature, and amount of mineral admixtures. Several elements, such as mineral admixture, percentage of mineral admixture, percentage of crystalline admixture, kind of exposure, etc., considerably impact the strength [9,10]. Due to the nonlinear interplay of the components, it is difficult to develop semi-empirical or empirical equations for the SHC strength model. Moreover, the degree of interaction and non-linearity between the relevant elements remains unclear.

Consequently, ANNs are used to create prediction models for SHC strength. In addition, no models were developed, and no significant research happened for predicting the strength of the SHC using ANN by considering the parameters mentioned above at the time. This makes the current study unique and highly advantageous for the research fraternity working on SHC.

3. Methods

Material characteristics were modelled using ANN. Kekez and Kubica [11] developed a concrete stress-strain model based on ANN. Mukherjee et al. [12] modelled and enhanced the mechanical properties of metal matrix composites using ANN. Chopra et al. [13] combined genetic programming (GP) and ANN to construct prediction models for concrete strength. Using ANN, they found that the Levenberg-Marquardt (LM) training function generated the most accurate forecasts of concrete strength. In addition, many studies [9,10,14] have focused on applying ANN modeling to improve the properties of concrete and other composites. In this study, the compressive strengths of SHC were predicted using ANN modeling. MA, PMA, PCA, and TE all influence compressive strength. The resultant parameters correspond to compressive strength (Fc).

ANN models selected and trained based on earlier research were used to analyze the trial results. The data analysis revealed a significant connection between the ANN-predicted values and the experimental values using root mean square error to assess the predictive power of the models (RMSE). ANN has capabilities that are useful for modelling complex problems and solving those using conventional methods and mathematics [15,16]. ANN acts like a black box. The back propagation approach of ANN is applicable to the majority of civil engineering applications [17] because of its simplicity. To train an ANN using a supervised learning technique (such as back propagation), the rights of connections between nodes must be defined [18]. An error function is reduced iteratively by minimizing the sum of squared errors between the actual outputs and the calculated outputs. A typical ANN has three layers: the input layer, the output layer, and the hidden layer. The thresholds and connecting weights may be modified to produce an LM network [19] after sample training. During training, the LM network stores information on the strength of the weight matrix and impacting variables. The Network then generates an output based on the input parameters [20–27]. There are five components to ANN-based modelling: (1) data collection and analysis, as well as issue description; (2) selection of the architecture; (3) determination of the learning process; (4) network training; and (5) network testing for generalization. The appropriateness of the ANN model was assessed using three statistical criteria. This comprises the root mean squared error (RMSE) and coefficient of determination (R^2). In addition, testing and training data are represented by related images to evaluate the link between experimental and model outcomes.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=i}^{N}(t_i - t_{io})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - o_i)^2} \tag{2}$$

Where,

N = Number of datasets

ti = Target output

oi = Network output

tio= Average of target output

To prepare a predictive model for concrete strength, a multi-layered feed-forward network trained with Levenberg–Marquardt function was used. The development approach of an ANN has been shown in Fig. 1.

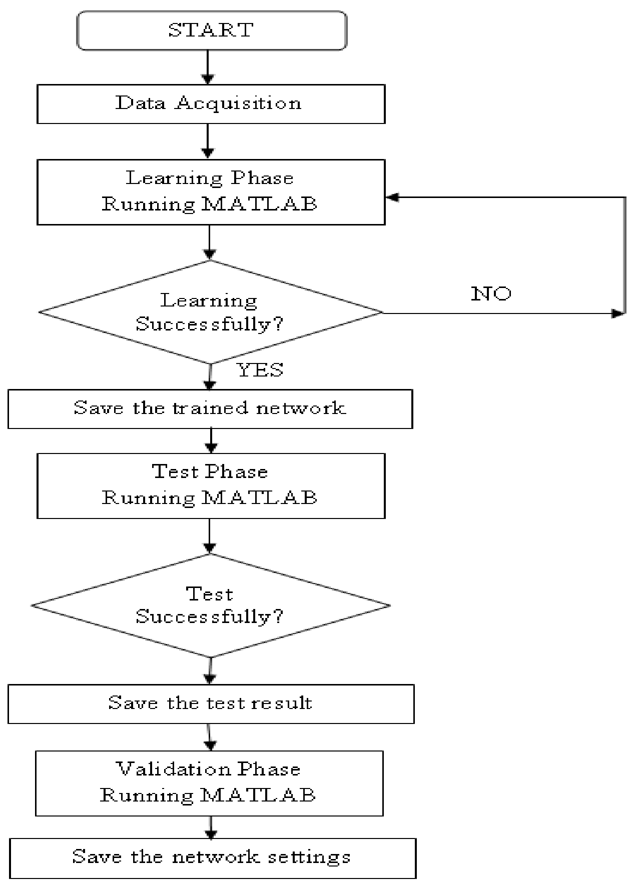

Fig. 1. ANN development approach.

3.1. Development of data sets of ANN

For developing a prediction model, a comprehensive strength data set that accounts for the microstructural factors that govern SHC behaviour are necessary. 100 SHC mixes were used in experiments to generate the required data set. The impact of mineral admixture, mineral admixture percentage, crystalline admixture percentage, and exposure type on the SHC strength characteristics was examined for each combination. The data sets were randomly divided for use in neural network training (75 percent), validation (15 percent), and testing (15 percent). Table 1 presents an assortment of common statistics.

Test Program

The various parameters studied were:

1) Mineral Admixtures (MA)

2) Percentage in Mineral Admixture (PMA)

3) Percentage in Crystalline admixture (PCA)

4) Type of exposure (TE)

Table 1
Parameters Data Set.

Data Sets	**S. No.**	**Mineral admixture (MA)**	**Percentage of mineral admixture (PMA)**	**Percentage of crystalline admixture (PCA)**	**Type of exposure (TE)**	**Compressive Strength (MPa)**
Training Data Sets	1	1	0	0	8	35.6
	2	1	0	0	9	34.32
	3	1	0	0	11	31.11
	4	2	5	0	8	42.13
	5	2	5	0	9	41.35
	6	2	5	0	11	39.05
	7	2	10	0	8	54.31
	8	2	10	0	9	53.88
	9	2	10	0	11	48.29
	10	2	15	0	8	47.77
	11	2	15	0	9	45.63
	12	2	15	0	11	44.56
	13	3	10	0	8	39.35
	14	3	10	0	9	37.41
	15	3	10	0	11	34.02
	16	3	15	0	8	50.92
	17	3	15	0	9	48.38
	18	3	15	0	11	38.22
	19	3	20	0	8	48.56
	20	3	20	0	9	46.55

	21	3	20	0	11	36.44
	22	4	10	0	8	32.81
	23	4	10	0	9	29.77
	24	4	10	0	11	23.56
	25	4	20	0	8	34.6
	26	4	20	0	9	31.11
	27	4	20	0	11	26.3
	28	4	30	0	8	33.25
	29	4	30	0	9	30.26
	30	4	30	0	11	24.55
	31	5	20	0	8	44.13
	32	5	20	0	9	43.35
	33	5	20	0	11	41.05
	34	5	30	0	8	56.31
	35	5	30	0	9	55.88
	36	5	30	0	11	50.29
	37	5	40	0	8	49.77
	38	5	40	0	9	47.63
	39	5	40	0	11	46.56
	40	1	0	1.1	8	88.17
	41	1	0	1.1	9	86.83
	42	1	0	1.1	11	63.22
	43	2	5	1.1	8	89.03
	44	2	5	1.1	9	87.41
	45	2	5	1.1	11	63.51
	46	2	10	1.1	8	92.29
	47	2	10	1.1	9	89.55
	48	2	10	1.1	11	65.32
	49	2	15	1.1	8	90.17
	50	2	15	1.1	9	88.36
	51	2	15	1.1	11	64.35
	52	3	10	1.1	8	88.91
	53	3	10	1.1	9	87.52
	54	3	10	1.1	11	63.47
	55	3	15	1.1	8	91.56
	56	3	15	1.1	9	89.03
	57	3	15	1.1	11	64.88
	58	3	20	1.1	8	89.42
	59	3	20	1.1	9	88.11
	60	3	20	1.1	11	63.82
	61	4	10	1.1	8	85.04

	62	4	10	1.1	9	77.27
	63	4	10	1.1	10	71.41
	64	4	10	1.1	11	61.87
	65	4	20	1.1	8	89.35
	66	4	20	1.1	9	85.15
	67	4	20	1.1	10	72.98
	68	4	20	1.1	11	63.82
	69	4	30	1.1	8	78.17
	70	4	30	1.1	9	79.25
Validation Data Sets	71	4	30	1.1	10	72.13
	72	4	30	1.1	11	62.66
	73	5	20	1.1	8	89.96
	74	5	20	1.1	9	89.25
	75	5	20	1.1	10	75.92
	76	5	20	1.1	11	65.98
	77	5	30	1.1	8	93.25
	78	5	30	1.1	9	90.12
	79	5	30	1.1	10	78.25
	80	5	30	1.1	11	69.72
	81	5	40	1.1	8	91.67
	82	5	40	1.1	9	88.65
	83	5	40	1.1	10	77.12
	84	5	40	1.1	11	68.66
	85	1	0	0	10	33.87
	86	2	5	0	10	39.98
	87	2	10	0	10	52.67
	88	2	15	0	10	44.91
	89	3	10	0	10	35.18
	90	3	15	0	10	46.47
Testing Data Sets	91	3	20	0	10	43.47
	92	4	10	0	10	27.6
	93	4	20	0	10	29.22
	94	4	30	0	10	28.11
	95	5	20	0	10	41.98
	96	5	30	0	10	54.67
	97	5	40	0	10	46.91
	98	1	0	1.1	10	72.77
	99	2	5	1.1	10	74.57
	100	2	10	1.1	10	77.89
Note :- 1 -No Admixture; 2 -Silica fume; 3 -Metakaolin; 4 -Fly ash; 5 -GGBS; Type of Exposure Indication: 8 - WI; 9 - WD; 10 - WC; 11 - AE.						

3.2. Preparation of concrete specimens

Self-healing studies were conducted on a pre-cracked concrete cube specimen of 100 mm × 100 mm × 100 mm size. After 28 days of aging, a controlled injury was inflicted on the concrete using a compression test to initiate the formation of structural fissures. During compression, a test setup for the production of cracks and the specified goal width of the crack (0.01–0.4 mm) were monitored using an optical micrometer calibration ruler. The surface was divided prior to cracking. Here, a maximum fracture width of 0.05 mm was created. After 42 days, a compressive testing machine was used to evaluate the concrete's self-healing. The effect of varied durations of exposure to air exposure (AE), water contraction (WC), wet-dry cycles (WD), and water immersion (WI) conditions on through-crack compressive stress and the possibility of various combinations to promote self-healing were examined.

3.2.1. Input and Output data sets

The present work aimed to design an SHC strength predictive model that can predict the strengths for a particular input (MA, PMA, PCA and TE). The compressive strength (Fc) was the corresponding output parameter. Therefore, for this model, the input vector was:

IP = {MA, PMA, PCA, TE}

And the output vector was:

OP = {Fc}

Table 2 and Table 3 depict the input and output parameters, respectively, normalized within the 0 to +1 range with the aid of appropriate scaling or neutralization factors.

Table 2
Input data sets.

Node Number	Input parameters	Minimum value	Maximum value	Mean
1	Mineral Admixture (MA)	1	5	3.307
2	Percentage of Mineral Admixture (PMA)	0	40	17.30
3	Percentage of Crystalline admixture (PCA)	0	1.1	0.55
4	Type of exposure (TE)	8	11	9.50

Table 3
Output data sets.

Node Number	Output parameter	Minimum value (MPa)	Maximum value (MPa)	Mean
1	Compressive Strength (F_c)	25.56	93.250	59.488

4. Results

4.1. Network training

The architecture was determined, and the network was trained to assess the output-to-input correlation. The training was undertaken using MATLAB software, and Figure 2 depicts the convergence of the solution. Using just 100 data sets for network training, the Network learned to accurately predict concrete strength, which was confirmed using training (75 percent), validation (15 percent), and testing (15 percent). Testing a network involves examining parameters that were not used during training. Fifteen data sets that had not been used during network training were utilized during network testing. The network-based projected values for these data sets are comparable to their experimental values. Therefore, the ANN model may be used to anticipate the intensity of SHC (Figure 4).

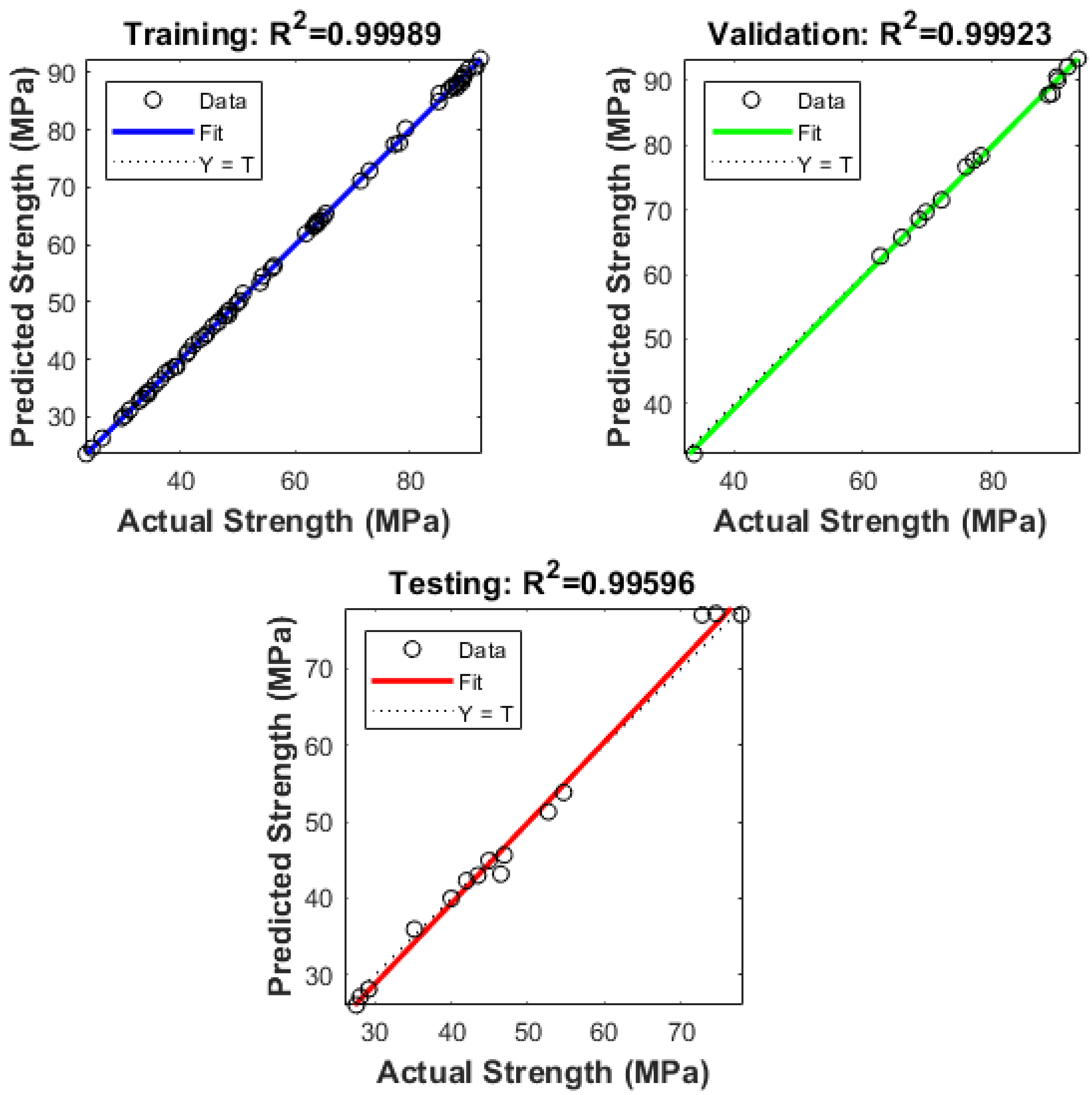

Fig. 2. Correlation between predicted and actual compressive strength.

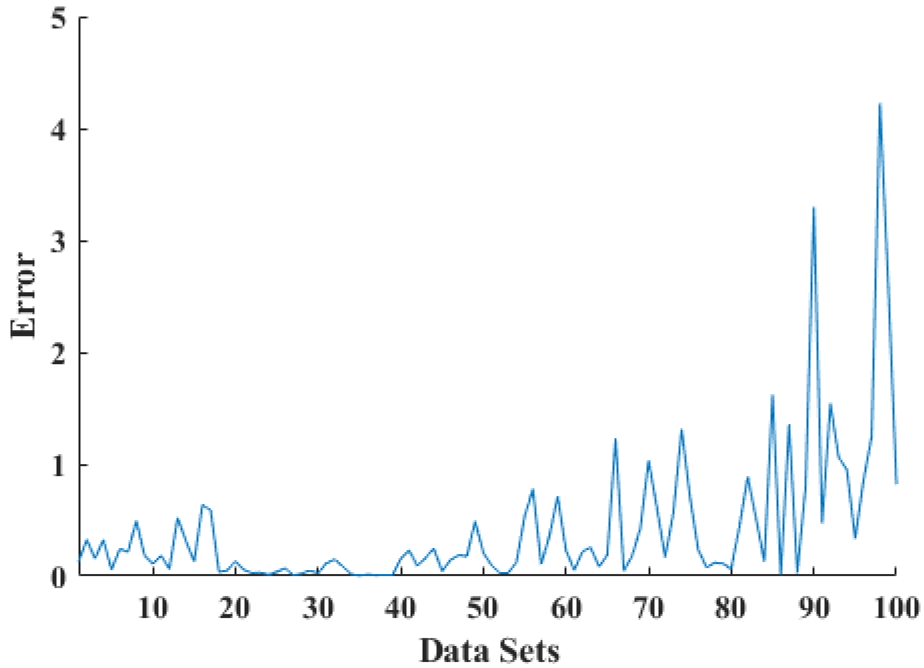

Fig. 3. Illustration of absolute error in experimental and predicted data.

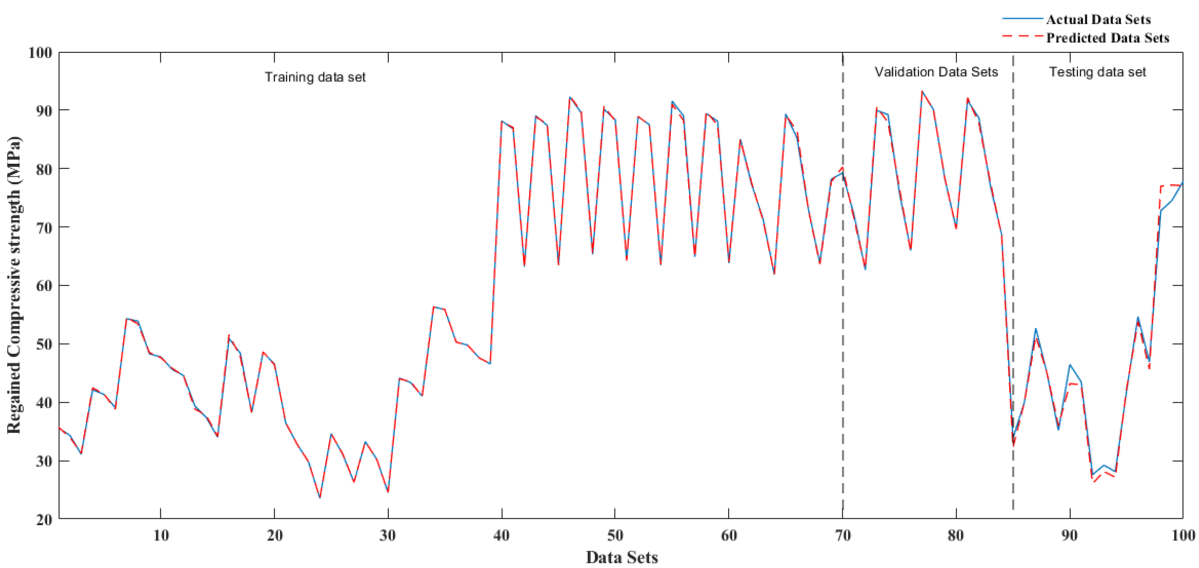

Fig. 4. Testing dataset for regained compressive strength.

4.2. ANN model development

The number of layers in a network, the number of neurons in a layer, the activation function of each layer, and the connection between layers are determined by ANN architecture. The ideal ANN design is determined by the nature of the network's problem. Therefore, the optimal design of an ANN is entirely governed by its application domain. The architecture of an ANN is dictated by the number of networks used for testing and training in various circumstances (Fig 5). MATLAB was used to analyze neural networks (2019a).

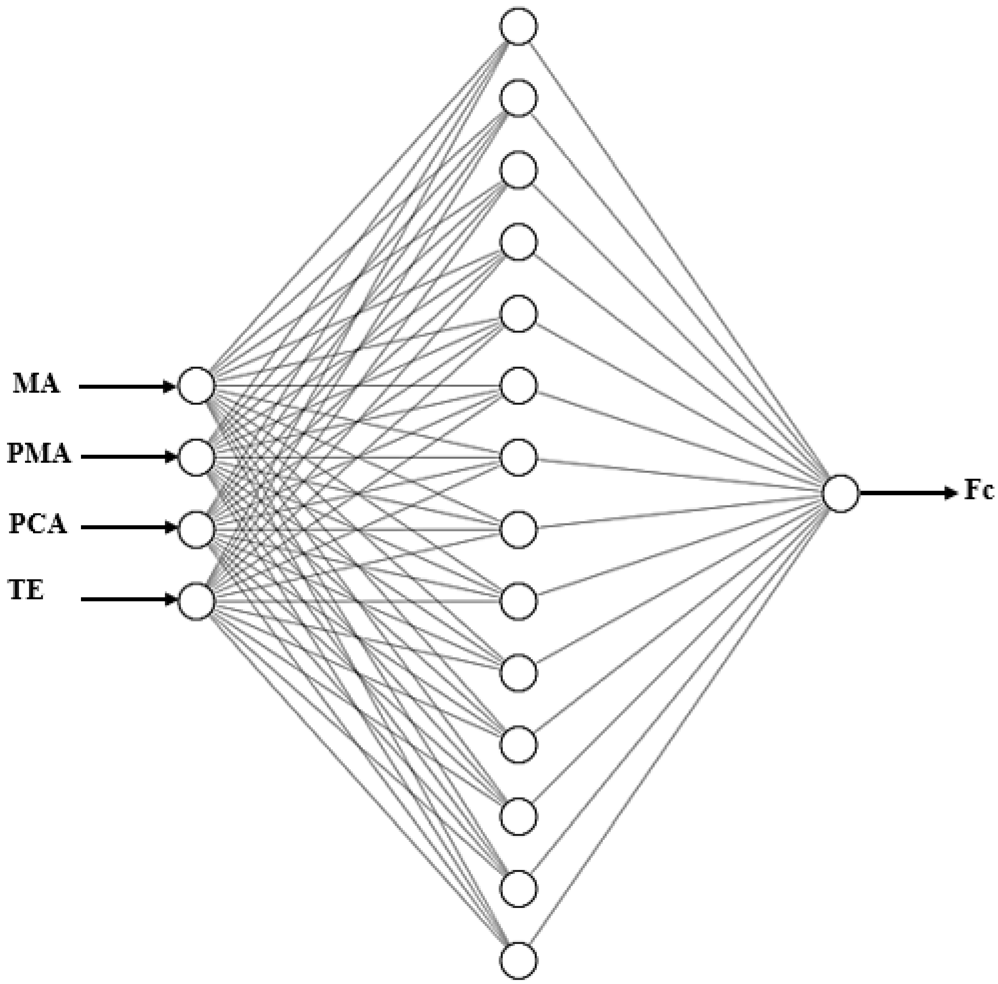

Fig. 5. ANN model architecture.

The values of parameters used in this research are as follows:

- Number of input layer unit = 4.
- Number of hidden layers = 1.
- Number of first hidden layer units = 14.
- Number of output layer units = 1.
- Learning algorithm = Levenberg–Marquardt (LM)

In addition, test networks with one or two hidden layers and a number of hidden nodes were used to compare the aforementioned methods. If the number of nodes in a network is very small, it may not be suitable for training or educational purposes. With a high number of nodes, computation time may increase [28–34]. Alternatively, a high number of nodes and layers may help minimize the number of training input samples required. Even if such a network performs badly on fresh test samples, showing that its generalization is severely affected, the data structure of the problem must be considered when establishing the network size. The approach of trial-and-error must be used to identify the number of hidden nodes, which, for the majority of applications, should be fewer than the number of training samples [35–41]. The networks were trained to minimize the difference between goal output and ANN output. As the objective of network training was to identify the correction weights (hidden neurons) that could reduce MSE in the shortest period of time, the training operation has concluded. Since hidden neurons or connection weights are used to store information, increasing their number allows the network to collect more data [42]. Table 4 shows that each network trained with a single hidden layer differs considerably in terms of computational time and accuracy.

Table 4
The R^2 and RMSE statistics.

	Training	Testing	Validation
R^2	0.99989	0.99596	0.99923
RMSE	0.99450	0.99548	0.99982

Due to low relative testing error and low testing and training RMSE, the ANN using the Levenberg-Marquardt method was the optimal choice. RMSE and R^2 values were determined by comparing planned and actual data with the supplied equation. 1 and 2, Figure 3 depicts a correlation between anticipated and actual data for testing and training models in terms of compressive strength. Figure 4 depicts the entire database, including predicted and observed outputs, and the absolute error for each data point to highlight the model's error percentage. As seen in the graph, the expected and actual outputs were comparable, and the frequency of maximum error was minimal. Approximately 80% of the predicted values have errors of less than 5MPa. Data from the training, validation, and testing phases were very similar, demonstrating a high capacity for generalization and accurate prediction of new data. During the process of addressing the data overfit, which validated the performance of three models, the predicted values of all models approached zero.

5. Discussion

Artificial neural networks can learn, generalize, and generate solutions from natural instances and experiences. This characteristic enables the ANN to serve as a tool for resolving some complex issues for which no information is accessible about their operational approaches. The research proved that ANNs are effective for civil engineering challenges. In this work, a multi-output ANN was created to predict the concrete mix composition of SHC based on criteria that are effective and determinants of concrete quality, taking into account these factors. To achieve this objective, 100 unique S-HC combinations with MA, PMA, PCA, and TE property characteristics were compiled from the scientific literature. The data was then separated into three sections. The first portion consisted of 70 data sets used to train the ANN, the second consisted of 15 data sets used to verify the trained ANN. The last consisted of 15 data sets used to test the trained and validated ANN model. After these procedures, the ANN was able to understand the issue and predict the SHC concrete mix composition from the data set. The correlation between real data and the anticipated outputs of the ANN model was 95.35 percent for training data, 94.87 percent for testing data, and 74.66 percent for validation data, which is an acceptable result. This is a significant achievement in terms of ANN model problem learning. Here, the generated ANN model learned 95% of the training data and reacted accurately to 95%

of the validation and test data. Notably, one of the most important findings of the completed investigation is that the results of ANN with LM networks seem to be practically independent of the learning method and number of hidden nodes (as long as this number is in the acceptable range determined by the widely used heuristics). This claim is supported by the results of ANN training in each of the investigated situations, which show a high coefficient of determination for each training, validation, and testing set. This is further reinforced by the positive outcomes of training, testing, validation data sets, and MSE and R^2 adjustments. Despite the proposed ANN with LM network's strong predictive potential, one of the primary constraints of the investigation is undoubtedly the simple composition of the concrete samples. Future analyses should use physical samples with varying characteristics in order to extend the current models and make them more applicable in everyday life. By using an ANN model for the design of SHC, it is possible to minimize the process time and the number of trial mixes. Thus, an economical design technique may be used without material loss.

6. Conclusions

In this study, an ANN-based model was designed for the prediction of the comprehensive strengths of SHC. Among the experimental data, 100 data sets were used for ANN training. The following conclusions could be deduced from this work:

- Utilizing an ANN method, prediction models for the compressive strength of SHC were developed. The suggested models were empirical and based on a widely scattered collection of experimental data.
- With a strong correlation value of $R^2 = 0.9998$ for training, $R^2 = 0.9985$ for validation, and $R^2 = 0.9191$ for testing, ANN accurately predicted the SHC strength parameters. Consequently, when compared to the experimental data, all predicted values were very trustworthy and precise.
- From an engineering perspective, an ANN model might be used to identify SHC with an accuracy of 80%.
- Finally, by incorporating a principal component analysis into the development of the Artificial Neural Network technique, it should be possible in the near future to reduce the number of parameters to those identified as dominant, thereby reducing the number of laboratory tests required to predict the compressive strength of SHC.

Conflicts of interest

Authors declare that they have no conflicts of interest.

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