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ORIGINAL INNOVATION

Prediction of the compressive strength of lightweight concrete containing industrial and waste steel fibers using a multilayer synthetic neural network

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Abstract

The use of waste and industrial steel fibers as part of the materials used in concrete can increase resistance and reduce cost and air pollution. It also saves energy. One of the important measures for technical inspections and assessment of the existing condition of structures, especially bridges, which is the most important communication factor, is to check the compressive strength. Considering that the calculation of compressive strength in the laboratory is done with the intervention of human power and is undoubtedly affected by human error, we decided to use it through.

Predicting the mechanical properties of concrete reinforced with steel fibers based on artificial neural network models without the need to conduct any laboratory studies will save money in construction projects. Unlike classical methods in statistical theories, neural networks do not require any specific model or function along with limiting assumptions to linearize problems.

For this purpose, this research was done with the aim of compensating this problem and with the aim of building a neural network with high accuracy that can make the desired predictions with the least error. In this research, this modeling was done using artificial neural networks (ANN) and Levenberg algorithm. The data used to train the neural network was collected from 45 different mixing schemes. Then the compressive strength of the sample is determined experimentally. The parameters considered for the ANN inputs are the values of steel fiber, water, water-cement ratio, cement and superlubricant. The objective data of this study included the compressive strength of each of these mixing designs at the ages of 7, 28 and 60 days. Then, to design the neural network, 75% of the data were considered as training data, 15% as target data and 15% as validation data. The compressive strength of concrete samples made from waste steel fibers increases. One of the reasons for this result is the placement and uniform distribution of fibers in the cement matrix, or in other words, the optimal amount of desired fibers in concrete. For experimental information and data, results can be seen with the help of neural network in data analysis. It was observed that the validation is correlated with a correlation coefficient above 99% and the constructed neural network has sufficient accuracy and validity.

Keywords: Compressive strength, Synthetic neural network, Steel fibers, Concrete

1 Introduction

Today, the use of concrete in the field of structural issues is very widely used and one of the important materials in the construction of structures (Alshihri et al. 2019). Among the materials used in the construction of structures, concrete is considered more than other materials because of its suitable applications. Among the advantages of concrete, the use of which is increasing in structures, it can be mentioned its lower price, suitable hardness compared to steel, fire resistance and ease of implementation (Bui et al. 2020). One of the most important parameters to control in concrete structures is to ensure the compressive strength considered in concrete design during execution. Which is classified as one of the most important properties of concrete and it is necessary to estimate it at the right time.

Today, the use of concrete with higher strength that can withstand many deformations without failure is being considered. Extensive research is being done on increasing the strength of concrete with different fibers and even removing the reinforcement, so with the results obtained, it can be understood that adding steel fibers to smooth concrete increases its compressive strength and this increase in strength gradually. It is done gradually by adding different volume percentages and types of fibers. Also, by adding steel fibers in concrete, we can achieve a concrete with higher compressive strength, which is more economical, by increasing the number and size of rebars, or special considerations in the field of concrete mixing design (Li et al. 2022).

Predicting the mechanical properties of concrete reinforced with steel fibers based on artificial neural network models without the need to carry out any laboratory studies will save a lot of money in projects. Unlike classical methods in statistical theories, neural networks do not require any specific model or function along with limiting assumptions to linearize problems (Ramkumar et al. 2020).

Due to the ever-increasing developments in the construction industry, there is always a need to present new methods. On the other hand, determining concrete resistance parameters in a short time and with acceptable accuracy is one of the challenges facing the construction industry. Advances in computer science in recent years have introduced very practical and fast methods into the field of civil engineering and especially the estimation of concrete resistance parameters. In this research, by studying and examining existing algorithms such as Levenberg algorithm and artificial neural networks, it is possible to train an optimal network that can predict the resistance properties of concrete with minimal error.

2 Background research

In 2018 Alton et al. used neural network to estimate lightweight concrete containing steel fibers. For this purpose, cement grade of 35, 400 and 450kg/m3 was used in the mixing designes. In this research, the effect of different amounts of fibers on lightweight concrete was tested. In their experiment, they used fibers at the rate of 10, 20, 30,40,50,60kg/m3. 127 cylindrical samples with dimensions of 300*150mm were made in the laboratory. Their input parameters to the neural network included steel fibers, water, water-cement ratio, sand, gravel and super lubricant. The compressive strength of concrete could be measured in the laboratory by adjusting the laboratory materials. The specific dry weight of sand and gravel was measured in the laboratory as 1.15 and 0.92 kg/cm3, respectively. The fibers used in this experiment had a diameter of 0.75mm and a length of 60mm and a tensile strength of 1050 N/mm2. The results show that the neural network provides a suitable estimate of the data. Neural network can provide more appropriate estimation of data even in case of better training. In this research, due to the high correlation coefficient and the variety in the selection of different parameters, it can be expected that the neural network has more variety in solving different problems than the complex statistical methods (Altun et al. 2018).

To estimate the compressive strength of concrete containing steel fibers used the artificial neural network method in 2015 was another research that was done in this field. Based on the information they had, they designed their neural network based on the lowest error rate or MSE and the highest correlation coefficient or R. The results of their research show that the use of the neural network with the Gauss–Newton algorithm has performed well in this research with a slight difference, and the obtained predictions have a very good correlation with the real data (Uysal and Tanyildizi 2015).

In another research in 2019 Hameed MM studied Prediction of compressive strength of high-performance concrete: hybrid artificial intelligence technique. In the last decade, various methods were used to predict the behaviour of concrete. Meanwhile, the use of neural network has the lowest cost and the most efficiency. It was shown that the use of neural network has a small error. And after many tests, it was found that the results of the laboratory are in good agreement with the results of the neural network (Hameed and AlOmar 2019).

The sensitivity of constituent materials and density of concrete as network inputs and the compressive strength of concrete as the test target or output is study by Erdel In 2013. The neural network predicts and measures the 28-day compressive strength of concrete. In his research, Erdal made the mean square of the error as the evaluation criterion of the network in such a way that the least amount of error indicates the proper performance of the network. In this research, the results show that the artificial neural network measures the data with high accuracy and low error (Erdal 2013).

In 2020 Nagarajan D et al. study on a comparative prediction models for strength properties of LWA concrete using artificial neural network. In this study, Artificial Neural Network (ANN) model is constructed to predict the compressive strength, split tensile strength and flexural strength of lightweight aggregate concrete made of sintered fly ash aggregate. An empirical relationship between the compressive strength, split tensile strength, and flexural strength was developed and compared with that of experimental results. The models were formulated based on results obtained from laboratory experiments. The variables considered in the study are the quantity of cement and water-cement ratio. Feed forward neural network and Levenberg–Marquardt back propagation algorithm were used for training algorithm in ANN. Amongst the total data, approximately 70% of the data was considered for training, 15% for testing and the remaining 15% has been considered for validation. The developed models had more accuracy with minimum error and had a higher correlation with the correlation coefficients of 0.916 and 0.955 were obtained for the

Fig. 1 The scheme of using artificial neural network in mixing designes

training and testing data of compressive strength prediction, 0.949 and 0.937 respectively for split tensile strength prediction, 0.926 and 0.928 respectively for prediction of flexural strength. The models were compared with the experimental data's, and the results were discussed (Nagarajan et al. 2020).

In 2023, Pakazad et ell, investigate the Comparison of various machine learning algorithms used for compressive strength prediction of steel fiber-reinforced concrete. The least contributing factors include the maximum size of aggregates (Dmax) and the length-to-diameter ratio of hooked ISFs (L/DISF). Several statistical parameters are also used as metrics to evaluate the performance of implemented models, such as coefficient of determination (R2), mean absolute error (MAE), and mean of squared error (MSE). Among different ML algorithms, convolutional neural network (CNN) with R2 = 0.928, RMSE = 5.043, and MAE = 3.833 shows higher accuracy. On the other hand, K-nearest neighbor (KNN) algorithm with R2 = 0.881, RMSE = 6.477, and MAE = 4.648 results in the weakest performance (Pakzad et al. 2023).

According to the research of others, the use of neural network regarding the estimation of compressive strength of concrete containing waste steel fibers has not been done so far. For this purpose, in this research, the construction of concrete with waste steel fibers and the estimation of compressive strength were investigated by using neural network.

3 Design of neural network

The use of neural networks to model the mechanical properties of each type of concrete can produce very appropriate and accurate results, and by using neural networks to predict concrete strength only once using the modeled laboratory results and achieve instant and accurate resistance prediction (Asteris and Mokos 2020). It is done properly and reduces many concrete sampling costs. It is very beneficial to use these models to further investigate the effective parameters on all types of concrete. The use of more characteristics of aggregates, the type of cement used and the conditions of making the samples, among other input parameters, makes the prediction of resistance more accurate. In this research, to predict the compressive strength of concrete made with polymer fibers, perceptron model artificial neural networks and its combination with particle mass algorithm (to optimize the percentage of fiber consumption) have been used. Particle swarm optimization algorithm has been introduced with other names such as particle swarm algorithm and bird algorithm. The schematic diagram of how to use the neural network is shown in Fig. 1.

4 The data used to test the artificial neural network

In order to collect the required data, the library method is used in such a way that a wide range of valid articles are studied and finally, after removing a series of inappropriate data, 45 samples from the design of lightweight concrete mixes containing waste and industrial steel fibers are considered for neural network modelling.

The data in Table 1 is intended as the input of the neural network, which is used to build and optimize the network.

5 The method of using artificial neural network of Multilayer Perceptron (MLP)

The number of neurons in the input layer is 11 neurons, after which 11 inputs will be induced into the network, and the output includes one neuron, which is the compressive strength of reinforced concrete with steel fibers and waste fiber. The Fig. 2 shows the method of working with a multilayer perceptron artificial neural network.

To separate test data and training data randomly by the program, so that 75% of the data is used for the training process, 15% of the data is used for testing, and 15% is used for validation. Was taken the input layer receives the input data and sends it to the hidden layer neurons (10 neurons).

6 Data used in neural network

In order to predict the compressive strength of concrete mixed with different amounts of water, the amount of steel fibers, water, the amount of coarse grain, the amount of fine grain, the amount of cement and also the age of concrete were considered in Table 2 and the compressive strength of their concrete was also estimated. The increasing of cement content from 250 to 450 kg/m3 at middle levels of slump. Mixture proportions for 1 m3 of concrete [kg/m3].

The mixes containing hooked industrial steel fibers and their 28-day compressive strength (tested by 150 mm cubic samples) were collected from the literature (Han et al. 2019; Zhu et al. 2019; Al-Baghdadi et al. 2021; Atiş and Karahan 2009; Caggiano et al. 2017; Graeff et al. 2009; Hu et al. 2018; Leone et al. 2018; Martinelli et al. 2015). Some of the mixes were omitted because of lacking the information of mixing components (such

Table 1 Neural network input data

Input parameter	Input data range	
	max	min
fine grain (P1) (kg/m3)	1230	685
fine grain (P2) (kg/m3)	931	0
Maximum diameter p3 coarse grain (mm)	20	0
Cement (P4) (kg/m3)	608	180
Water P5 (kg/m3)	320	158
Industrial steel fibers (P6) (ratio, %)	3	0/5
Waste steel fibers (P7) (ratio, %)	3	0/5
super lubricant (P8) (ratio, %)	12	4
Sample height (P9) (mm)	160	150
Sample length (P10) (mm)	150	40
sample width (P11) (mm)	106/07	28/28

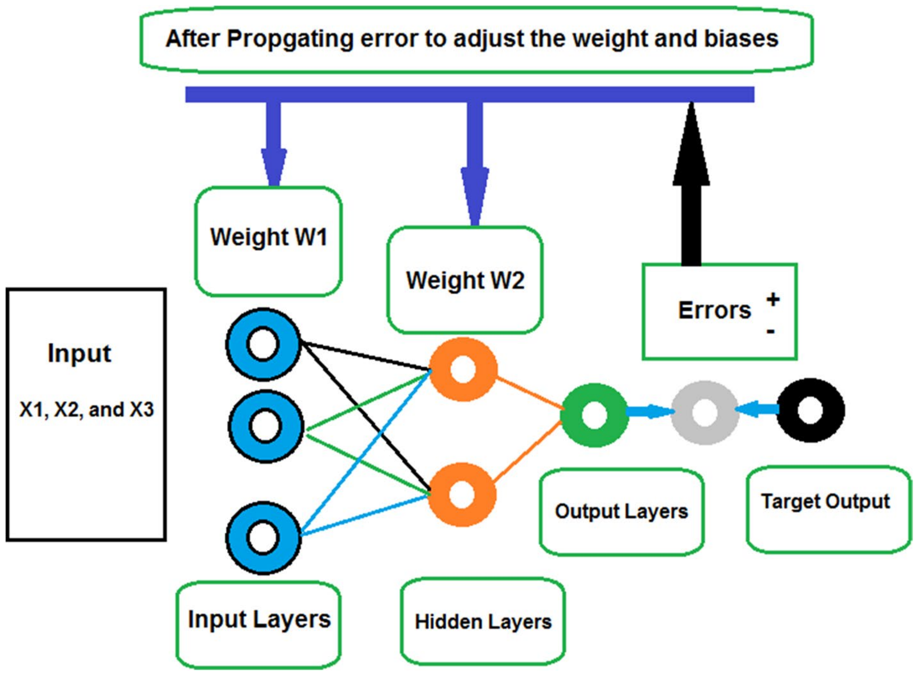

Fig. 2 The method of working with a multilayer perceptron artificial neural network

as fine aggregates, super plasticizer, etc.). Eventually, 45 mixes were selected for training the models in predicting the compressive strength of steel fiber reinforced concrete. The input information for training the neural network is the data of each of the mixing designs and the target data of compressive strength of concrete samples at the ages of 7, 28 and 60 days are considered, in total 135 data are considered as targets.

7 The structure of the neural network

The training of this neural network has been done with the help of Levenberg algorithm and using MATLAB software. In the structure of this network, 75% of the data is randomly considered as training data, 15% as target data and 15% of data as validation. As shown in the Fig. 3, the constructed neural network is stopped after 5 times of training and this point is considered as the best point to stop the training. The Fig. 3 shows the degree of correlation in each of the stages of training, evaluation and testing for the selected neural network.

Figure 4 shows the correlation between laboratory data and neural network regarding the data of training, evaluation and compressive resistance test in neural network.

The neural network built in this research has 6 hidden layers which was obtained by trial and error, 11 input layers, and 1 output layers, and the training results of this network are the final output layer. The desired neural network is trained with Levenberg algorithm.

The coefficient of determination or R^2 is a measure that provides information about the goodness of fit of model. In the context of regression it is a statistical measure of how well the regression line approximates the actual data. It is therefore important when a

Table 2 Data used in neural network

Mix number	component					
	Cement (kg/m3)	**Steel fibers (kg/m3)**	**Water (kg/m3)**	**Gravel (kg/m3)**	**Sand (kg/m3)**	**Super lubricant (kg/m3)**
1	350	0	105	1180	850	1/4
2	332/5	17/5	105	1150	850	1/5
3	315	35	105	1150	850	2/52
4	297/5	52/5	105	1150	850	2/87
5	280	70	105	1150	850	3/1
6	350	0	140	1100	820	1/05
7	332/5	17/5	140	1100	820	1/17
8	315	35	140	1100	820	1/75
9	297/5	52/5	140	1100	820	2/34
10	280	70	140	1100	820	2/8
11	350	0	175	1015	810	0
12	332/5	17/5	175	1015	810	0/24
13	315	35	175	1015	810	0/48
14	297/5	52/5	175	1015	810	0/84
15	280	70	175	1015	810	2/04
16	400	0	120	1100	850	1/82
17	380	20	120	1080	850	2/64
18	360	40	120	1080	850	3/68
19	340	60	120	1080	850	4/02
20	320	80	120	1080	850	5/29
21	400	0	160	1000	830	0/7
22	380	20	160	1000	820	0/88
23	360	40	160	1000	820	1/06
24	360	40	160	1000	820	0/89
25	320	80	160	1000	820	2/25
26	340	80	0	980	750	2/25
27	320	0	20	980	750	0/24
28	400	20	20	980	750	0/24
29	380	40	40	980	750	0/6
30	360	60	60	980	750	0/96
31	340	80	80	980	750	1/33
32	320	0	0	1050	800	2/54
33	450	22	22/5	1050	800	6/36
34	427/5	45	45	1050	800	13/89
35	405	67/5	67/5	1050	800	16/21
36	382/5	90	90	1050	800	23/74
37	360	0	0	950	800	0/71
38	428/5	22/5	22/5	920	800	1/2
39	405	45	45	920	800	1/2
40	385	67	67/5	920	800	1/8
41	362	90	0	900	800	2/4
42	452	0	22/5	900	700	00
43	425	22/5	45	900	700	00
44	410	45	67/5	900	700	0/06
45	352	67	90	900	700	0/55

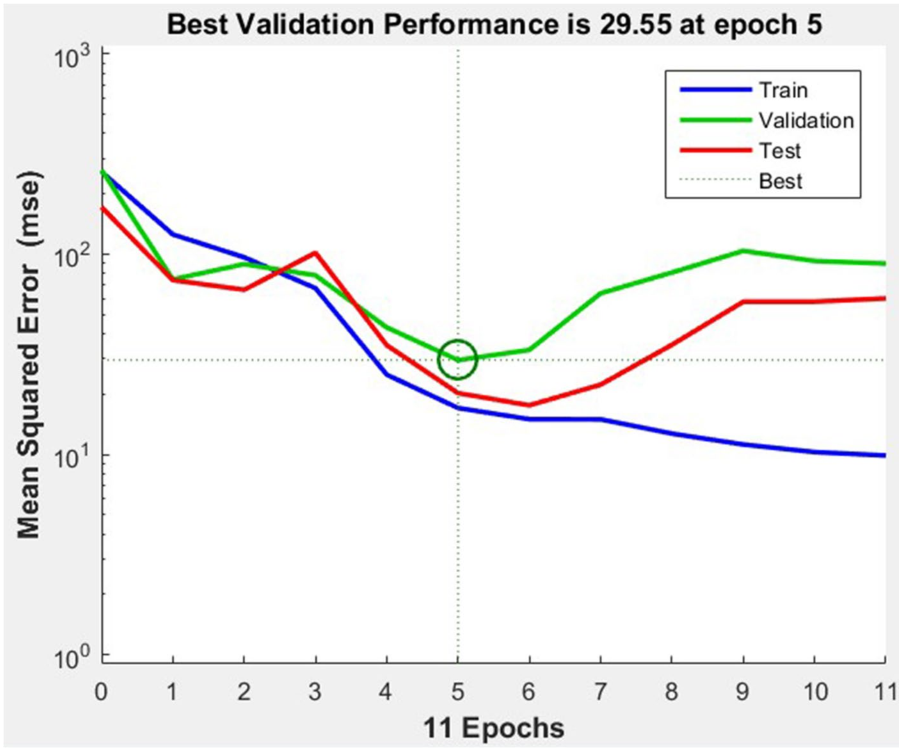

Fig. 3 The stopping point of the training in the desired neural network

statistical model is used either to predict future outcomes or in the testing of hypotheses. There are a number of variants, the one presented Eq. 1 widely used:

$$R^2 = 1 - \frac{Sum\ squared\ regression\ (SSR)}{total\ sum\ of\ squres\ (SST)} = 1 - \frac{\sum (y_i - \tilde{y}_i)^2}{\sum (y_i - \overline{y})^2} \tag{1}$$

Validate this statement just for some point in order to achieve the coefficient:

For point (0.2, 0.2)

$$\hat{y} = 1 * Target + 0.0022 = 1 * 0.2 + 0.0022 = 0.2022$$

The actual for y is 0.2.

$$r_1 = y_i - \hat{y}_i = 0.2 - 0.2022 = -0.0022$$

For point (0.3, 0.35)

$$\text{Residual} = \text{actual y value} - \text{Predicted y value}$$
$$\hat{y} = 1 * Target + 0.0022 = 1 * 0.3 + 0.0022 = 0.3020$$

The actual for y is 0.35.

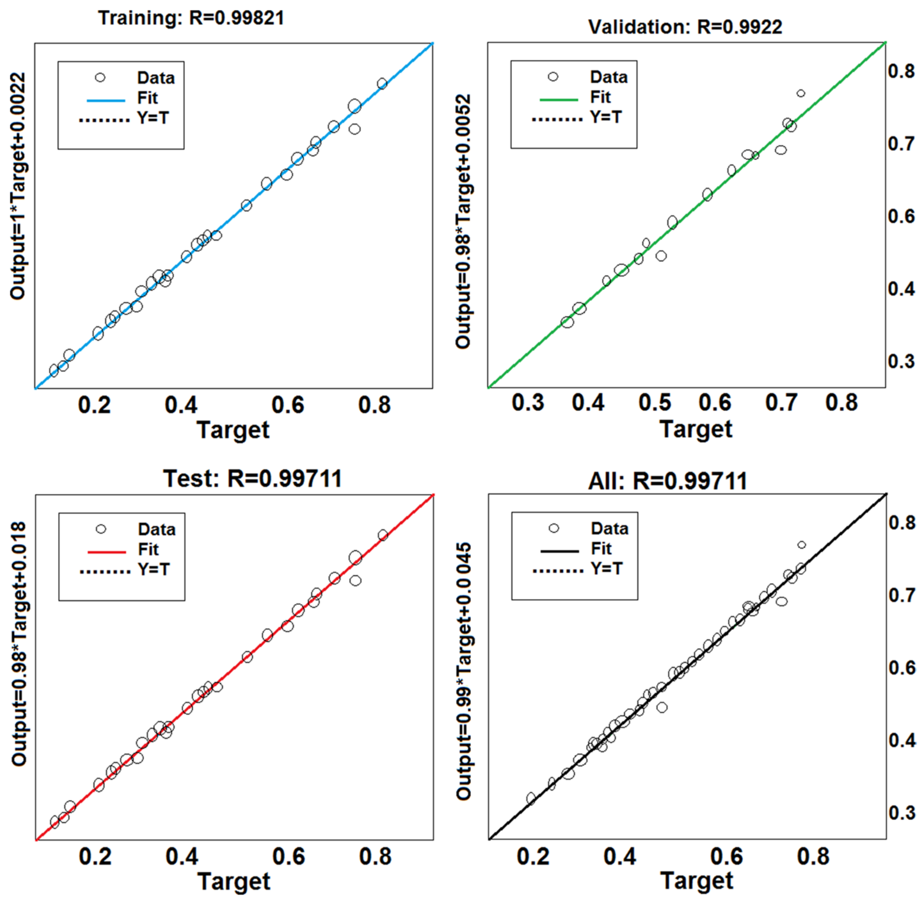

Fig. 4 Linear relationship between measured and estimated values of compressive strength using Levenberg's algorithm

$$\text{Residual } = \text{actual y value} - \text{Predicted y value}$$
$$r_1 = y_i - \hat{y}_i$$
$$= 0.35 - 0.3022 = 0.0478$$

To find the residuals squared we need to square each of r_1 and r_2 and sum them.

$$\sum(y_i - \hat{y}_i) = \sum r_i$$
$$= r_1^2 + r_2^2 = (-0.022)^2 + (0.0478)^2 + \cdots = 0.0039688$$

To find $\sum (y_i - \bar{y})^2$ first we need to find the mean of the y values.

$$\bar{y} = \frac{\sum y}{n} = \frac{0.2 + 0.35}{2} = 0.275$$

Now we can calculate $\sum(y_i - \bar{y})^2$

$$\sum(y_i - \bar{y})^2 = (0.2 - 0.275)^2 + (0.35 - 0.275)^2 + \cdots = 2.21125$$

Therefore

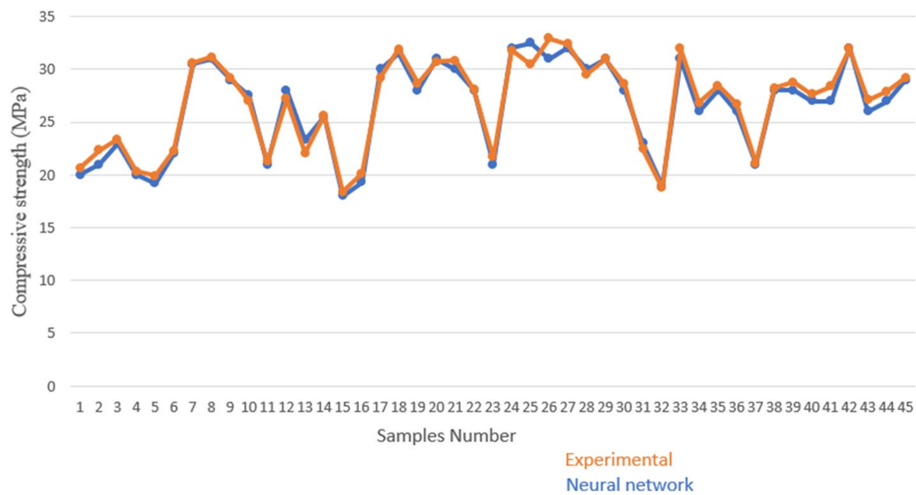

Fig. 5 Comparison of predicted values and experimental values 7-day compressive strength

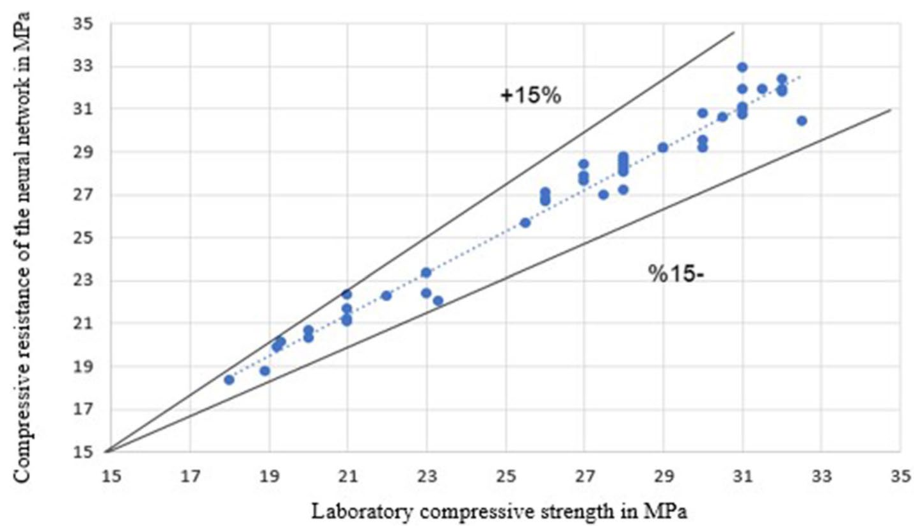

Fig. 6 Comparison between predicted values and experimental values of 7-day compressive strength

$$R^2 = 1 - \frac{Sum\ squared\ regression\ (SSR)}{total\ sum\ of\ squres\ (SST)} = 1 - \frac{\sum(y_i - \tilde{y}_i)^2}{\sum(y_i - \bar{y})^2} = 1 - 0.00179 = 0.99821$$

Correlation of training, testing and validation data shows that these data are correlated with each other with correlation coefficients of 0.99, 0.99 and 0.99%, respectively, and it shows that the well-designed neural network has the ability to predict the desired outputs.

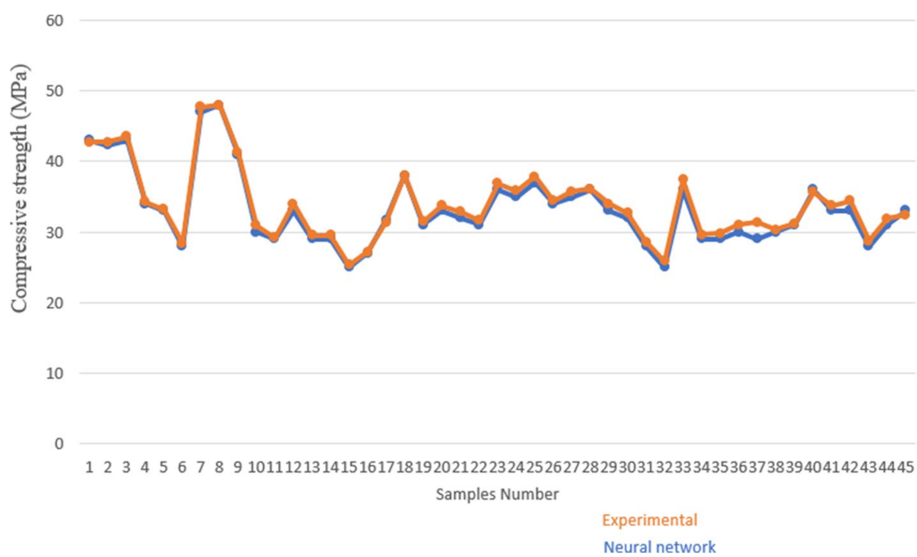

Fig. 7 Comparison of predicted values and experimental values 28- day compressive strength

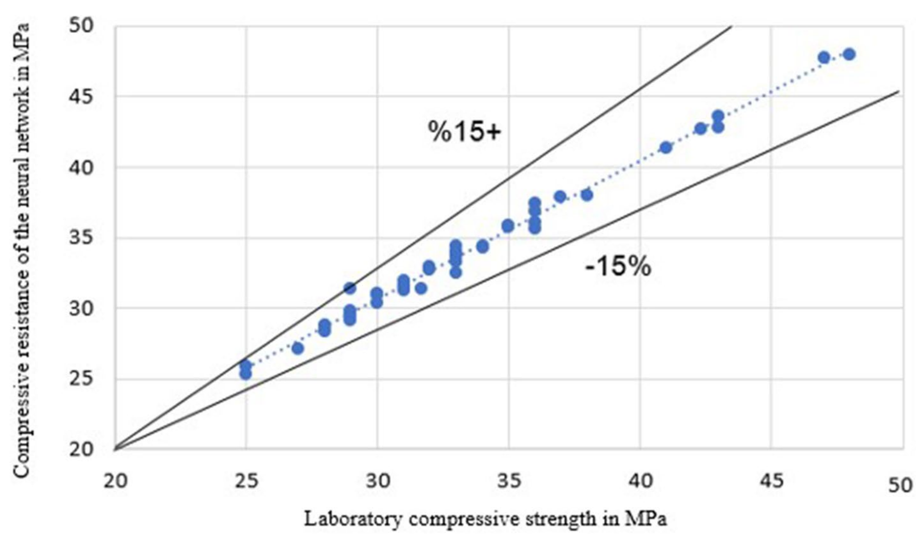

Fig. 8 Comparison between predicted values and experimental values of 28-day compressive strength

8 Comparison of designed neural network results and laboratory results in predicting compressive strength

The results of the 7-day compressive strength estimated with the help of the neural network constructed with the results of the laboratory compressive strength are shown in Fig. 5.

As shown in Figs. 5 and 6, the 7-day compressive strength estimated by artificial neural network is very close to the compressive strength obtained in the laboratory.

The results of the 28-day compressive strength estimated with the help of the neural network built with the results of the laboratory compressive strength are given in Fig. 7.

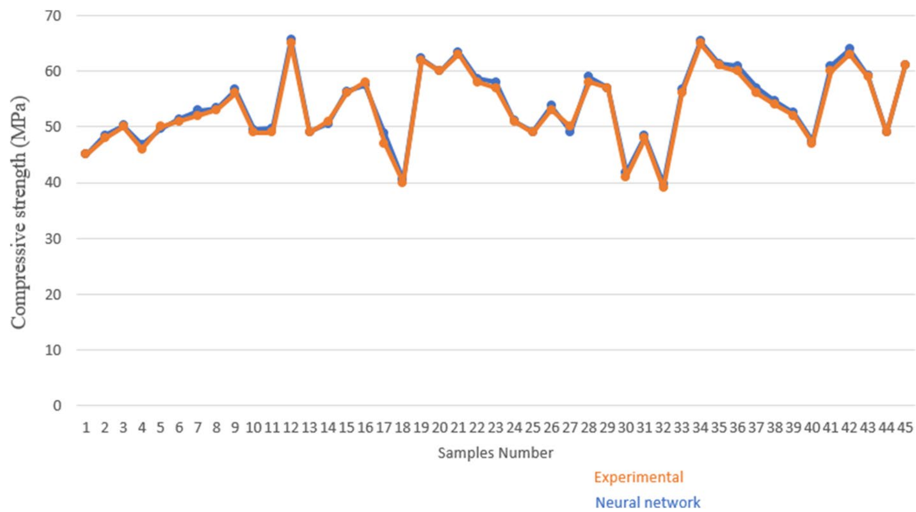

Fig. 9 Comparison of predicted values and experimental values 60-day compressive strength

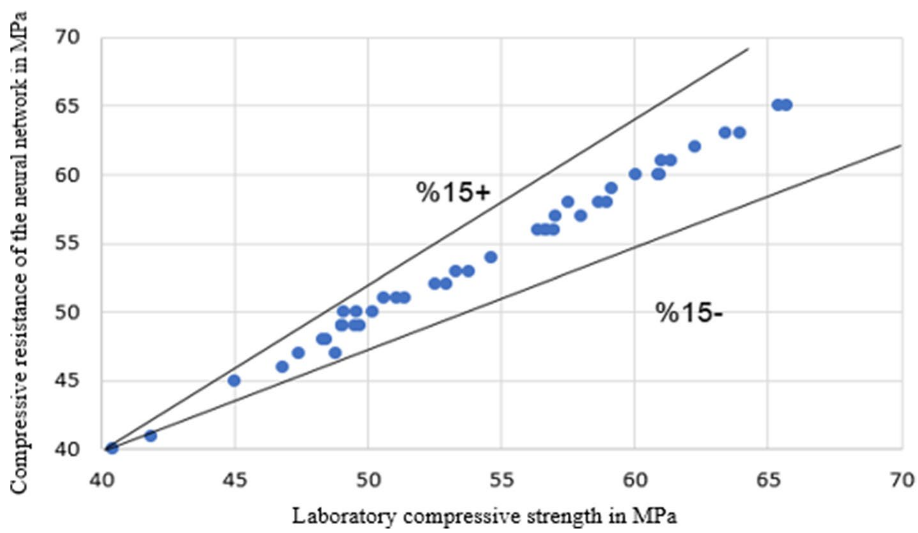

Fig. 10 Comparison between predicted values and experimental values of 60-day compressive strength

As shown in Figs. 7 and 8, the 28- day compressive strength estimated with the artificial neural network is very close to the compressive strength obtained in the laboratory.

The results of the 60- day compressive strength estimated with the neural network built with the results of the laboratory compressive strength are given in Fig. 9.

As shown in Figs. 9 and 10, the 60-day compressive strength estimated with the artificial neural network is very close to the compressive strength obtained in the laboratory.

9 Conclusion

The results shows that the ANN has the ability to estimate the compressive strength of concrete at different ages.

The use of steel fibers in reinforced concrete increases the compressive strength of the samples, and this increase in strength has been done gradually. Also, the increase in compressive strength resulting from this increase in the percentage of fibers can be considered due to the proper placement of fibers and their uniform distribution in the cement matrix, or in other words, the optimal number of desired fibers in the concrete itself.

The compressive strength ANN model was trained by using the Levenberg algorithm, The input information for training the neural network is the data of each of the mixing designs and the target data of compressive strength of concrete samples at the ages of 7, 28 and 60 days are considered, in total 135 data are considered as targets. Out of this number, 101 samples were used for training and 20 samples were used for testing. These samples were randomly and experimentally selected and after normalizing the data, they were given to the grid to estimate the compressive strength of concrete. The predicted values were fairly close to the experimental results for both the training and testing data sets in the proposed model. The compressive strengths predicted by the neural network have shown a correlation of about 99% for the test data, which indicates the proper performance of the neural network in data analysis.

Predicting the mechanical properties of concrete reinforced with steel fibers based on artificial neural network models without the need to perform any laboratory studies can save a lot of costs in projects. Because experiment results and ANN.

Model exhibited good correlation, the proposed ANN is a valid alternative approach to prediction and programming using artificial neural networks.

Unlike the classic methods in statistical theories, neural networks do not need any specific model or function along with limiting assumptions to linearize the problem.

Authors' contributions

The first author (FN) initiated the idea, designed the study, conducted a brief literature survey, scrutinized the literature, participated in sequence alignment, and prepared a draft copy of the manuscript. The second author (AM) has collected the data, scrutinized the literature, categorized them according to the sequence, participated in sequence alignment, and designed the graphics & illustratons. All authors read and approved the final manuscript.

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The authors guarantee that the contribution is original (and has not been published previously), and is not under consideration for publication elsewhere.

Availability of data and materials

Not applicable. However, if any literature data is required, first author would provide them.

Declarations

Competing interests

We would like to declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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