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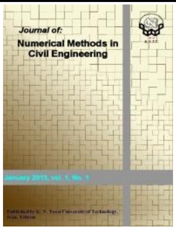

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Prediction of strength parameters of concrete containing different additives using optimized neural network algorithm

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Abstract:

In this research, a multilayer feed-forward backpropagation error neural network has been used to predict the strength parameters of a concrete sample containing different additives. To achieve the most optimal neural network structure, the strength parameters of the concrete have been evaluated for different neural network arrangements. Control criteria are the use of numerical values of performance, the correlation between training functions, Validation and testing in the neural network, gradient and results of regression diagram to determine the most optimal neural network structure. It was found that the function of the neural network largely depends on its geometric structure. Revealed by the research findings, the most optimal prediction of the neural network has occurred in the case of using three layers with 30 neurons in each layer in the neural network. In this case, the numerical value of the neural network performance and the regression were obtained as 58.5 × (10^{-9}) and 0.9846 , respectively. By determining the optimal neural network, different percentages of concrete raw materials based on the pre-performed experimental study are introduced to the selected neural network and the considered resistance parameters are predicted through residual analysis. According to the results, the differences between the predicted values of the neural network and the numerical values of the experimental study concerning the parameters of compressive, flexural, and tensile strength were also found to be equal to 1.68%, 1.92%, and 0.21%, respectively. Such a slight difference reflects the optimal accuracy of the chosen neural network in predicting the strength parameters.

1. Introduction

The determinative and effective parameters in the designing process involve compressive, flexural, and tensile strength of the concrete, while using concrete in various axial and bending elements needs to be considered as well. Experimental limitations, the high cost of additives, etc., do not always allow us to perform experimental studies designated to achieve the most desirable percentage of the composition of additives to obtain a concrete sample with the highest strength parameters.

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Also, considering the high importance of concrete structures can always reduce the damage and increase the safety and productivity levels of different types of structures using the most optimal concrete with ideal strength parameters. Thus, it seems reasonable to employ alternative methods to estimate the strength parameters of concrete for different percentages of constituent raw materials. Therefore, applying the neural network method seems a good choice.

A neural network is a large parallel processor consisting of simple processor units, and the most critical superiority compared to other intelligent systems is the power of learning from the environment and increasing efficiency during training. Figure 1 shows a model of a node containing the primary processing unit in a neural network and the governing mathematical model. X_{ij} are the input values of node j, W_{ij} is the network weights, f is the excitation function, b_j is the bias value, and O_j is the output value of node j.

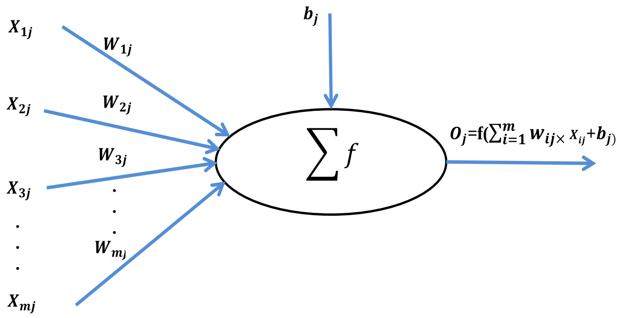

Fig.1: Function of neurons in the neural network.

In Generally, the neural network consists of five different parts, which include inputs, weights, bias, performance function and output. Inputs are the input information to the network, the weights are the effect of the input on the output, and the bias is the effect of the input of a fixed value of 1 on the neuron. Weights and bias are adjustable, and the performance function is determined by the network designer. In general, neural networks consist of three types of layers that are input layers, hidden layers and output layers. Figure 2 shows the general structure of the neural network.

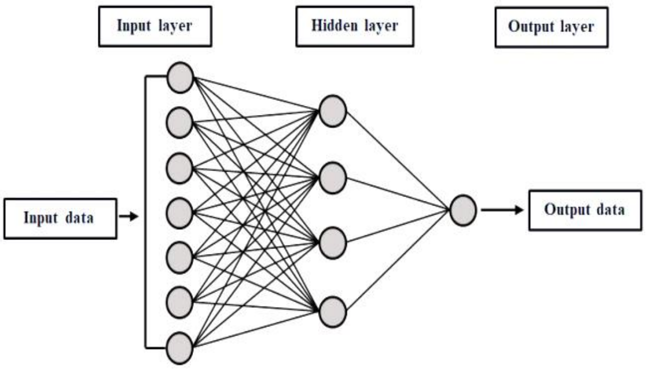

Fig. 2: neural network structure

Therefore, in recent years, the use of neural network methods to predict engineering parameters has been of great interest. Mahin Rousta and Boroujerdi (2011) [1] focused on predicting the stress-strain behavior of gravel materials using artificial neural networks. The parameters used in the network training of their study included grading characteristics, dry density, relative density, Los Angeles wear percentage, all-round (confining) pressure, strain, and deviatoric stress. The simulation results suggest that the proposed neural network is capable of predicting and determining the stress-strain behavior of the coarse aggregates. The performed sensitivity assessments also indicate very excellent compliance of the network behavior with the rules and principles of soil mechanics. Hence, the neural network presented in their study seems to be able to model the stress-strain curves of gravel materials using simple parameters usually defined in the early stages of explorations. Kyuchukova and Austin (2020) [2] utilized the artificial neural network to examine the effect of the presence of date kernel shells as aggregate on the compressive strength of concrete. They studied and evaluated fifty different concrete mixtures containing different ratios of date kernel shells, in which 80% of the samples were used for training and 20% of the samples were employed for evaluation and testing of the neural network. According to the study results, the numerical values predicted by the artificial neural network were found to be significantly correlated with the experiment results in estimating the compressive strength of concrete containing date kernel shell. Yoon et al. (2020) [3] studied and evaluated the mechanical properties of lightweight aggregates in concrete, including compressive strength and elastic modulus of the mixture, using an artificial neural network. They found that the numerical values predicted by the artificial neural network are highly accurate according to the results obtained from the linear and non-linear regression models. Zavertonik et al. (2016) [4] used artificial neural networks to model the air vacuum content in different superstructure (pavement) mixtures. The main goal of their study was defined as modeling the relationship between different parameters and air vacuum content in dense mixtures by employing multiple linear regression (MLR), in which the backpropagation error algorithm was used to build the neural network. Their results demonstrated that the examined neural networks had provided quite proper models to estimate the amount of air vacuum in the studied mixtures. Lazaruska et al. (2012) [5] reviewed the application of artificial neural networks in civil engineering. They specifically investigated the resistance of structural elements to fire. Comparing the results obtained from numerical studies with the findings from the prediction using the neural network method revealed that the artificial neural network method can be used as a powerful mechanism to determine the resistance of reinforced concrete columns against fire (especially in situations where experimental and numerical studies cannot be performed). In a study in 2012 [6]. Mortezaei and Kheiruddin (2012) [6] modeled and estimated the plastic joint length of reinforced concrete columns by artificial neural networks. They used artificial neural networks to analyze and examine the behavior of reinforced concrete columns at the component level, including determining the length of the plastic joint and obtained acceptable and optimal results. The plastic joint specifications, including the length of the plastic joint, were provided according to the results of 150 experiments on reinforced concrete columns and the proposed artificial neural network model which the specifications of the plastic joints can be obtained by presenting the necessary information to these networks in less than a few tenths of a second. The input data is divided into three training, evaluation, and testing categories, of which 70%, 20%, and 10% of the data are considered for them, respectively. A relation is provided by considering the calculated errors and the effect of each of the input parameters on the length of the plastic joint. The original measured values for the length of the plastic joint can be obtained using this equation.

Shafabakhsh et al. (2012) [7] focused on selecting the optimal artificial neural network algorithm to analyze the rigid pavement of the roads. The proposed analytical tool based on the results of artificial neural network models was in the form of a four-layer backpropagation neural network, consisting of two hidden layers and input and output layers, with 18 neurons and employing a cyclic transfer function. A regression rate of 0.99928 assures the use of accurate results obtained in other studies. Golnaraghi et al. (2019) [8] determined the most optimal neural network in their research study aimed at predicting the efficiency of various parameters. The neural networks examined in this study included Artificial Neural Network (ANN), General Regression Neural Network (GRNN), Backpropagation Neural Network (BNN), Radial Base Function Neural Network (RBFNN), and Adaptive Neuro-Fuzzy Inference System (ANFIS). Comparing the findings from each of the studied modes revealed that the use of the artificial neural network (ANN) method operates better than other modeling techniques. Mohammed et al. (2021) [9] evaluated and quantified the effect of nanoclay (NC) as an additive to cement paste. Considering qualification, the flow of slurry and stress at the failure of cement paste modified with nanoclay, non-linear regressions model (NLR), and Artificial Neural Network (ANN) technical approaches were used. The results have shown that the ANN model could predict the compressive strength of the testing data so carefully (R greater than or equal to 0.851). After that, a non-linear relation (NLR) was derived by using the same variables and the parameters were found via multiple regression. Similarly, the NLR model and ANN models could predict the rheological properties and compression strength of the testing data precisely. According to the experimental data sets, the NLR predicted the compressive strength very close to experimental data and the predictions were better than the ANN model. Al-Gburi and Yusuf (2022) [10], using ANN, investigated the effect of mineral additives on concrete strength. They found that the artificial neural network's results were so close to the previous experimental results. As a result, using an artificial neural network is very suitable to understand and predict the behavior of complicated data. Nafees et al. (2021) [11] in a study, considered the predictive modeling of mechanical properties of silica fume-based green concrete using artificial intelligence approaches. The values of statistical parameters indicated that all models can predict the compressive and split tensile strengths of concrete precisely. Finding the most careful model, the results of the machine learning models and the genetic programming (GEP) model are compared. External validation and sensitivity assessments were also carried out for additional assurance. R2 values were achieved using the best model (GEP) for compressive strength of 0.97 and for tensile strength of 0.93. Sharifi and Hosseinpour (2020) [12], in a study, present a predictive model-based ANN for compressive strength assessment of the mortars containing metakaolin. After that, to predict the compressive strength of mortars, which containing Metakaolin (MK), a new formula was presented using the constructed ANN model. It is observed that the formula can predict the compressive strength of the mortars incorporating Metakaolin (MK) with a slight error. Finally, to examine the effect of each predictive variable on the compressive strength of the mortars containing MK, Garson's algorithm as a sensitivity algorithm was employed. The results have shown that the binder-sand ratio is a more important parameter in determining the compressive strength of the mortars containing MK. Although some researchers such as adili et al. [13] have used other methods such as fuzzy systems to predict the mechanical properties of concrete, the appropriate accuracy and simplicity of the neural network have usually prioritized its use. As it seems, extensive studies have been performed the use of neural networks in solving various problems in the field of civil engineering [14-24]. Due to the complex structure of the neural network, determining the most optimal structure has a significant impact on the accuracy of the predicted response and optimization in the neural network.

In the present study, in order to predict the strength parameters of concrete containing different additives using an optimal neural network structure, first , the design of mixing a concrete sample containing different percentages of additives as input, and corresponding strength parameters as output parameters was taken from laboratory study [25]; and then, they used for training a neural network system. to achieve the optimal neural network function, the geometric structure of the network, including the number of the layers and neurons in each layer, is considered a variable. Therefore, considering 3, 4, and 5 middle layers and 10, 20, 30, and 50 neurons in each layer, activation functions, number of layers, and number of neurons in each layer was optimized using control criteria through trial and error *Also*, the geometric structure of the network, including the number of layers and number of neurons in each layer, are considered as variables. Then, through trial and error, for different values of the number of the layers and neurons, the neural network in predicting the three parameters of compressive, flexural and tensile strength of the studied concrete sample was performed by controlling the criteria of numerical value of neural network performance and regression. The most desirable neural network structure is obtained using the minimum numerical value of network performance and regression close to 1. After determining the most optimal geometric structure of the neural network, the considered strength parameters for the concrete sample with different percentages of additives are calculated by performing residual analysis. Hence, the predicted results through the optimal neural network and the results presented in the experimental study (reference 25) will be compared.

2. Materials and method

2.1 Data collection and normalization

The data studied in this research are derived from experimental study samples conducted by Agarwal et al. (2020) [25]. Various compounds have been used in this experimental study and the raw materials and compounds along with the weight of each component in Table 1 are provided for making concrete samples. As can be seen, the amounts of gravel, water, and superplasticizer are fixed in all combinations, and cement, nanosilica, coarse aggregates, and recycled materials each has 4 different numerical values. Thus, 256 possible and unique cases in this study can be assessed. However, due to a large number of possible cases, only 16 cases have been evaluated according to Table 2. Therefore, the values of the strength parameters will be predicted among these 16 cases.

Table 1: Primary materials for making different concrete samples [25].

Material	Unit	Weight			
Cement	kg/m^3	504.21	499.16	494.12	489.08
Nanosilica (NS)	kg/m^3	0	5.04	10.08	15.12
Sand	kg/m^3	683.24	683.24	683.24	683.24
Coarse Aggregate (CA)	kg/m^3	1108.13	886.5	664.87	443.25
Water	lit/m^3	141.63	141.63	141.63	141.63
Super Plasticizer	l/m^3	4.67	4.67	4.67	4.67
Recycled Aggregate (RA)	kg/m^3	0	221.6	443.25	664.87

Table 2: Selected studied modes to determine different strength parameters of concrete [25].

Model	NS	CA	RA	Cement	Water	Super Plasticizer
NS0RA0	0	1108.13	0	504.21	141.63	4.67
NS0RA20	0	886.5	221.6	504.21	141.63	4.67
NS0RA40	0	664.87	443.25	504.21	141.63	4.67
NS0RA60	0	443.25	664.87	504.21	141.63	4.67
NS1RA0	5.04	1108.13	0	499.16	141.63	4.67
NS1RA20	5.04	886.5	221.6	499.16	141.63	4.67
NS1RA40	5.04	664.87	443.25	499.16	141.63	4.67
NS1RA60	5.04	443.25	664.87	499.16	141.63	4.67
NS3 RA0	10.08	1108.13	0	494.12	141.63	4.67
NS3RA20	10.08	886.5	221.6	494.12	141.63	4.67
NS3RA40	10.08	664.87	443.25	494.12	141.63	4.67
NS3RA60	10.08	443.25	664.87	494.12	141.63	4.67
NS5RA0	15.12	1108.13	0	489.08	141.63	4.67
NS5RA20	15.12	886.5	221.6	489.08	141.63	4.67
NS5RA40	15.12	664.87	443.25	489.08	141.63	4.67
NS5RA60	15.12	443.25	664.87	489.08	141.63	4.67

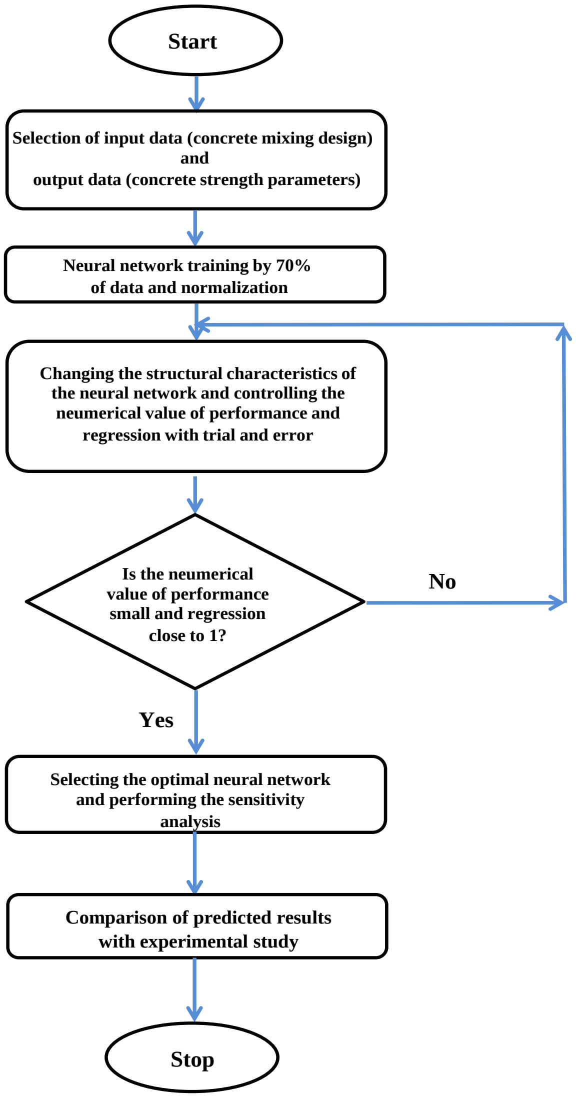

Fig.3: Research methodology flowchart.

We used 70% of the data for neural network training and 30% for neural network evaluation and testing.We normalized different datasets to increase the accuracy of the neural network so that all the data turned into a number between zero and one. Hence, the largest number is equal to 1 and the other numbers would be in the range of zero to one. Equation (1) was used to normalize the data.

$$U_{NORMAL} = \frac{(U_I - U_{MIN})}{(U_{MAX} - U_{MIN})} \quad (1)$$

In the present study, various criteria such as mean square error and number of learning cycles, gradient, momentum mass, and the numerical value of network performance as well as linear regression have been used to evaluate the efficiency of the neural network. Increasing the power of network generalization, the Cross-Validation method has been used. In this method, the data is divided into three sets: training, evaluation, and experimental. To find the best parameters for the model, the evaluation set is used as part of the inexperienced data in the control of the training process. Initially, the performance of the trained network in dealing with this data was evaluated according to the error indices, then the networks that performed well for the evaluation data were also studied for the experimental set. Finally, each parameter by which the network shows the best performance in simulation and prediction, is selected as the optimal parameter. Figure 3 shows the flowchart of the methodology of the research.

2.2 Neural network

The neural network used was examined in MATLAB software environment with “nntool” command with different numbers of layers and neurons by trial and error approach aimed at ultimately doing the most optimal prediction of the studied parameters. Various scenarios have been studied to build the neural network. Thus, the studied scenarios regarding the arrangement and formation of the neural network are given in Table 3. Accordingly, 12 different states (modes), including the number of different layers and the number of different neurons in each layer, were studied and analyzed by trial and error approach. The names of each of these simulation modes are presented in Table3.

Table 3: Different modes of neural network simulation

State No.	Abbreviation	Number of Layers	Number of neurons
1	Ffb310	3	10
2	Ffb320	3	20
3	Ffb330	3	30
4	Ffb350	3	50
5	Ffb410	4	10
6	Ffb420	4	20
7	Ffb430	4	30
8	Ffb450	4	50
9	Ffb510	5	10
10	Ffb520	5	20
11	Ffb530	5	30
12	Ffb550	5	50

3. Results and Discussion

Based on the research plan, we provide the performance graphs, gradients, and regression curves related to each of the 12 different neural network simulation modes aimed at determining the most optimal conditions for neural network simulation to predict the strength parameters of the studied concrete sample according to Table 2. Figure 4 shows the mean square of errors and the number of learning cycles used for 12 different neural networks. The greater correlation between the “Training, Validation, and Testing” functions, i.e., these three graphs are more uniform relative to each other, we will see the success of the neural network in predicting the examined parameter. Figure 5 illustrates the gradient, momentum mass, and evaluation controls for each of the 12 proposed neural networks. Finally, Figure 6 indicates the linear coefficient of data correlation (regression) related to different modes of the neural network. The closer this coefficient to the number 1, the higher the accuracy of the network in numerically predicting the parameters in question would be. The numerical comparison between control criteria aimed at determining the most optimal neural network among the 12 cases is presented in Table 4 according to the high number of discussed graphs. The numerical values of regression as the first controlling criterion should be considered. Thus, providing acceptable results when the regression is less than 0.9 is not acceptable. Therefore, modes 4, 6, 7, 9, 10, and 11 are considered unacceptable modes, which will be removed in the first control from the list of candidate neural networks (based on the results of Graph 4). The numerical value of the function will be addressed in the next control. The lower numerical values of the performance will bring us better results. Hence, modes 1, 8, and 12 are removed from the list of desirable neural networks due to their high numerical value. Thus, according to the latest control criterion, the greater correlation between the three functions of training, validation, and testing, the better result will be obtained. Therefore, among the three modes 2, 3, and 5, the highest correlation is related to mode 3 according to the diagrams in Figure 4. Thus, the most optimal neural network is a network that consists of three layers with 30 neurons used in each layer (Ffb330). The results obtained at this research stage indicate the very high sensitivity of the structure and geometry of the neural network to the predicted response. Therefore, based on the results of trial and error and based on the mentioned control criteria, the most desirable neural network is a network that consists of three layers and has 30 neurons in each layer. It should be noted that in the case of the diagrams presented in Figure 4, which show the changes in MSE versus the cycles, the training data are for the network training and the validation data have no effect on the training process. Also, validation data is often used to validate and find the appropriate number of training cycles. According to the neural network model related to Ffb330 mode, shown in Figure 4, if the neural network is trained with training data (blue curve), by increasing the number of cycles, the training data error will be decreased. Also, due to the trend of error and validation changes (green curve), it is observed that until cycle 4, the validation error decreased and then remained constant and unchanged. At this point, the most desirable network performance is achieved and training should be stopped. Based on the obtained results, it can be seen that the most optimal performance of the optimal neural network is related to the Ffb330 state, for the 4^{th} cycle, the functional error is 0.045 and the numerical value of that neural network (Ffb330) is equal to $58.5*10^{-9}$. Also, according to Figure 5 and for the selected neural network mode, the numerical parameter of the gradient and the momentum coefficient are 0.000194 and $10^{-10,}$ respectively. The correlation coefficient for the training curve, validation, evaluation and total data curve are presented in Figure 5. It can be seen that the linear regression correlation coefficient for the selected neural network Ffb330 is 0.9846. In fact, in this case, the regression line is really close to the line with a one-to-one slope. Also, the results presented in Figure 6 show that the degree of closeness in training data is much higher than the validation and evaluation data.

Table 4: Selecting the most optimal neural network according to the controlling criteria.

	Abbreviation	Perfor(10^{-9})	Gradient	Mu(10^{-10})	Reg
1	Ffb310	2360	0.00151	100	0.9304
2	Ffb320	4.15	0.000109	0.00001	0.9682
3	Ffb330	58.5	0.000194	1	0.9846
4	Ffb350	56300000	0.00045	10000	0.7902
5	Ffb410	0.352	0.000265	0.00001	0.9412
6	Ffb420	2150	0.00177	10	0.8578
7	Ffb430	6090000	0.104	1000000	0.8076
8	Ffb450	1040	0.00265	1	0.9767
9	Ffb510	195000	0.00143	100000	0.6366
10	Ffb520	3470	0.00339	1	0.8990
11	Ffb530	15000000	0.00189	1000	0.7107
12	Ffb550	109	0.000751	1000	0.9603

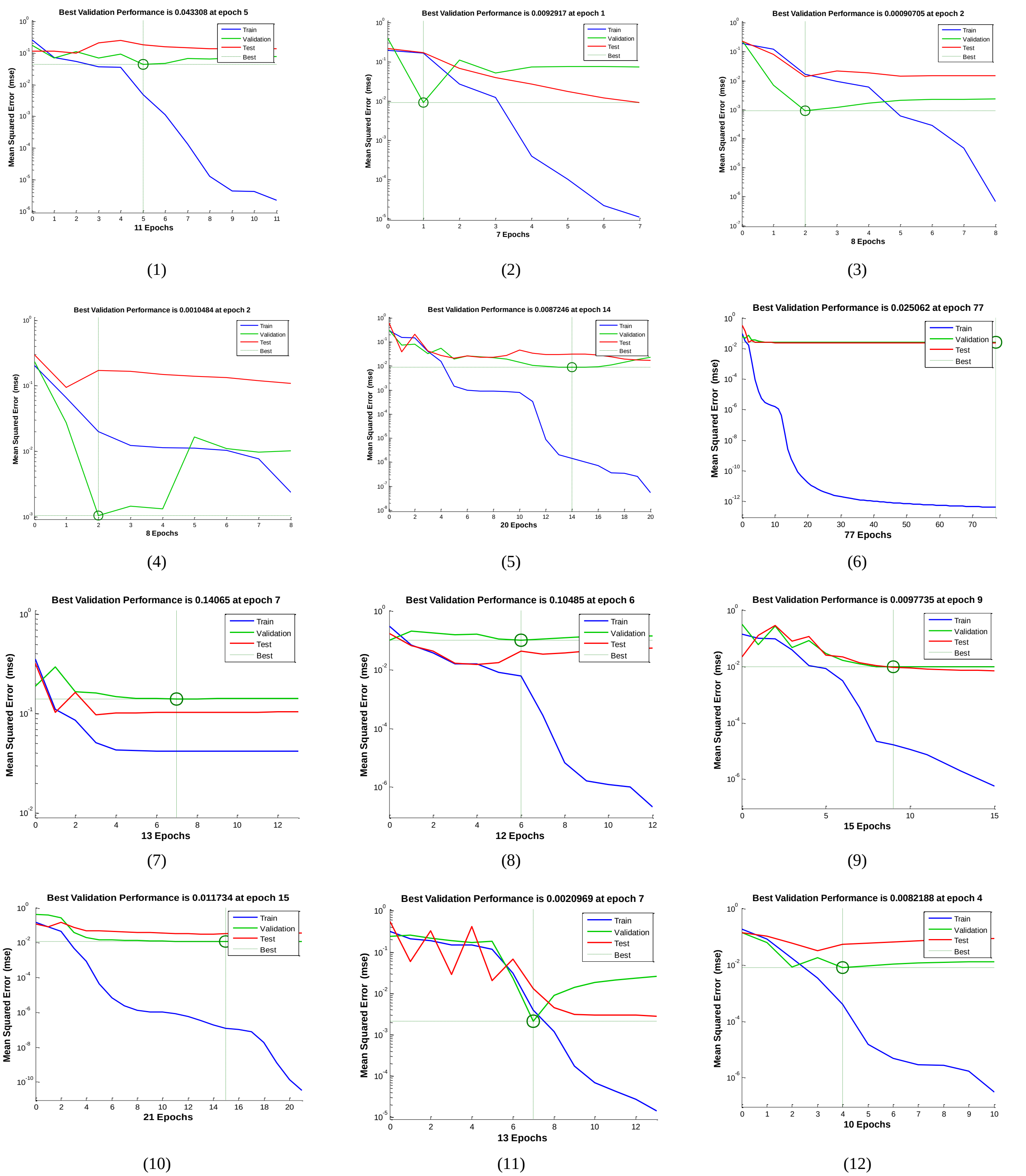

Fig. 4: The mean square of errors and the number of learning cycles used in the studied neural networks.

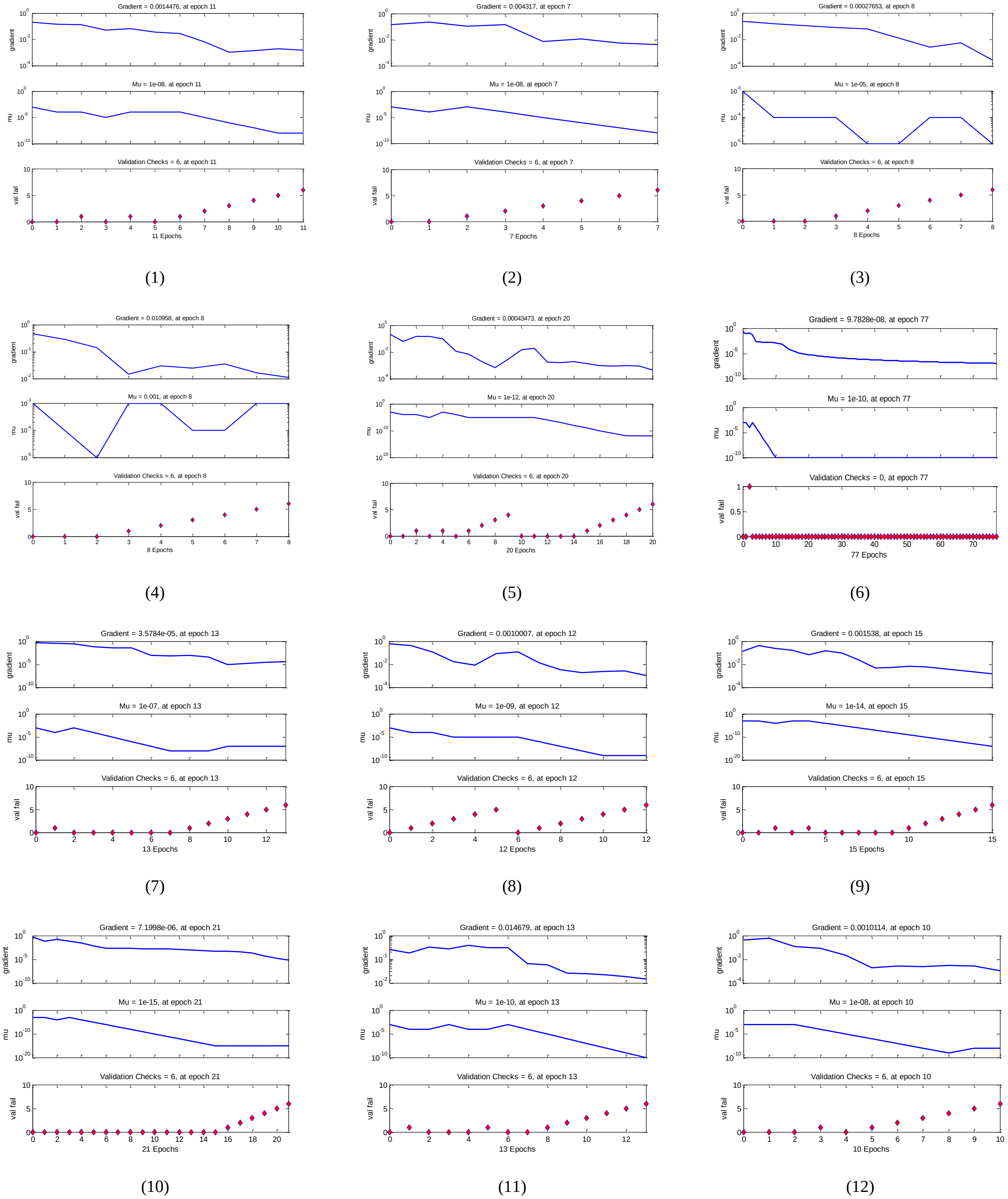

Fig. 5: The gradient, momentum mass, and evaluation controls related to neural networks used in the present study.

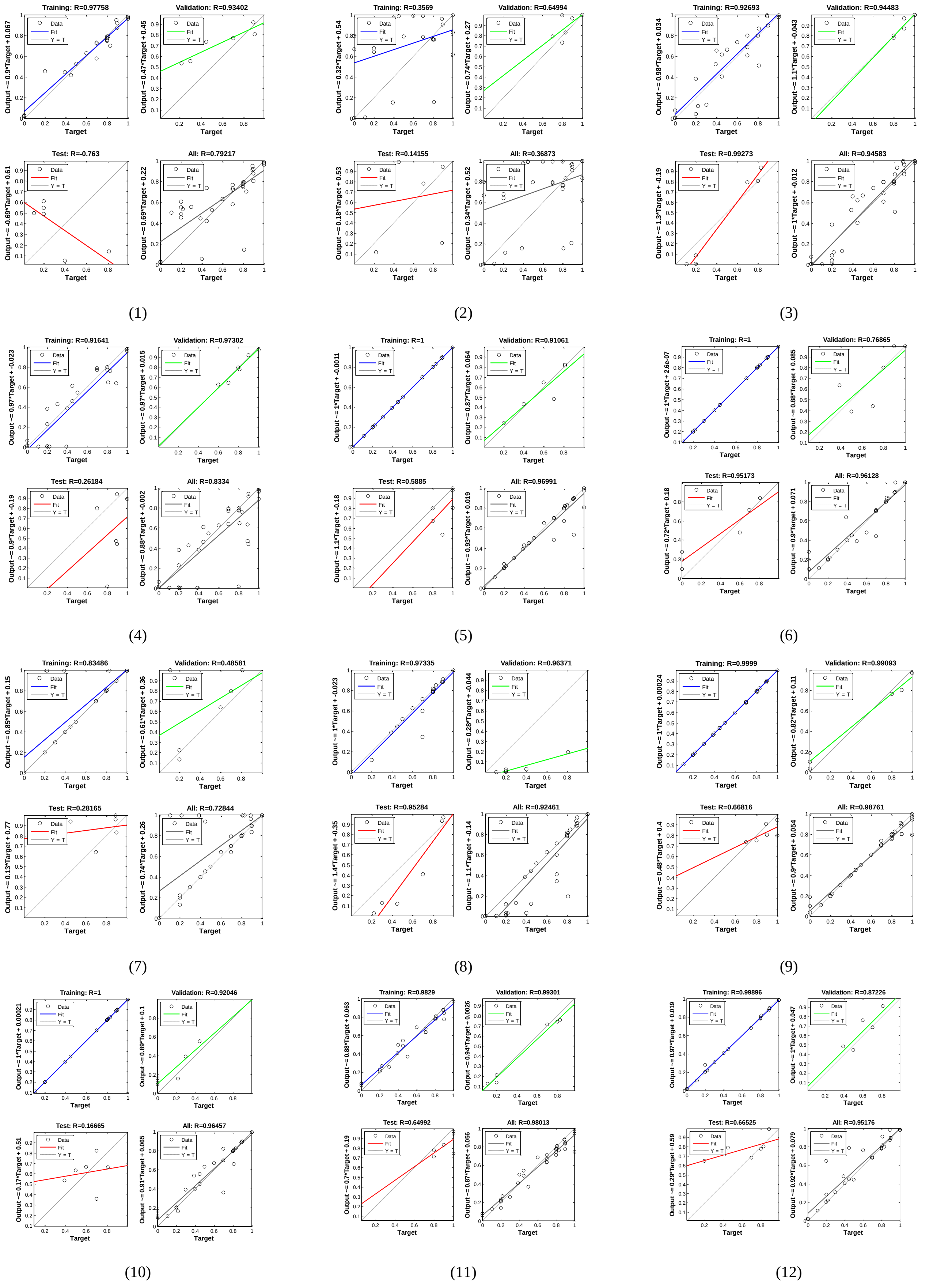

Fig. 6: The linear regression for training, validation, and testing functions for different neural network modes used in the present study.

3.1 Residual Analysis

After selecting the most optimal neural network, the residual analysis will be performed according to the data extracted from the experimental study [25], which included 16 different mixing designs. As mentioned before, 70% of the data was used for network training (12 mixing designs) and 30% was used for evaluation (4 mixing designs). Output parameters in the present study included 28-day compressive, flexural, and tensile strength of the concrete specimens. Therefore, in Table 5, the output parameters of the reference article [25] are compared with the values obtained from the Ffb330 neural network prediction. Figures 7-9 provide a comparison of flexural, compressive, and tensile strength between the outputs of the reference paper and the values calculated from the neural networks, respectively. According to the results of the residual analysis based on the flexural strength criterion of concrete (Figure 7), the difference between the results predicted by the neural network and experimental results varies in the range of 0.6-4.9%. Also, the range of difference between the results of neural network prediction and experimental study on the compressive and tensile strength of concrete is in the range of 0.6-2.9% and 0.3-2.5% respectively. On average, the difference between the results predicted by the neural network and experimental study on determining flexural, compressive and tensile strength of concrete is 1.68%,1.92%, and 0.21%, respectively. Thus, due to the high cost of experimental studies, it is advisable to predict the strength parameters of concrete with acceptable accuracy using the optimal neural network introduced in the presented study. In this way, the cost and time of experimental studies was significantly reduced. The comparison results of the flexural, compressive, and tensile strength among the outputs resulted from the reference paper and the calculated values from the neural network are provided in Figures 7 to 9, respectively.

Table 5: The numerical comparison of normalized output parameters of the neural network.

	Flexural Strength	Compressive Strength	Split Tensile Strength
Experimental	0.94	1	1
Neural Network	0.9999	0.9343	0.7538
Experimental	0.94	0.7	0.7
Neural Network	0.9999	0.8899	0.7695
Experimental	0.94	0.6	0.7
Neural Network	0.9996	0.8501	0.7331
Experimental	0.5	0.5	0.2
Neural Network	0.9914	0.7937	0.3995

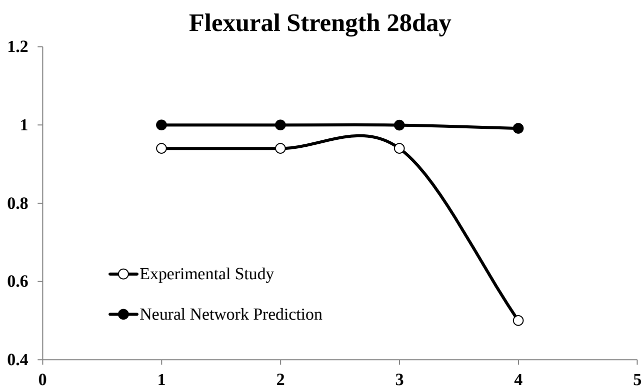

Fig. 7: The residual analysis of flexural strength

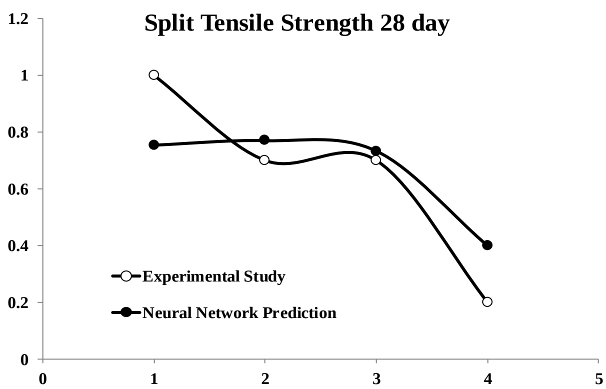

Fig. 9: The residual analysis of split tensile strength

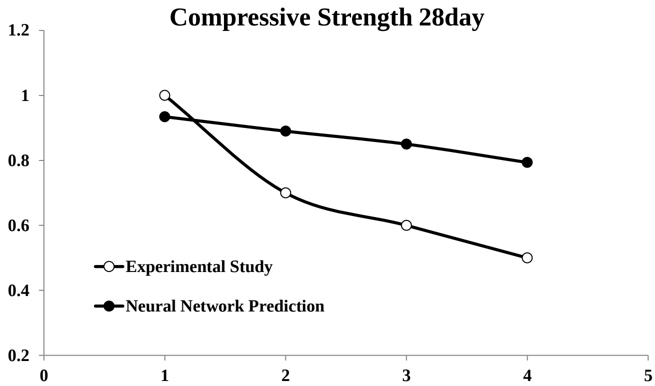

Fig. 8: The residual analysis of compressive strength

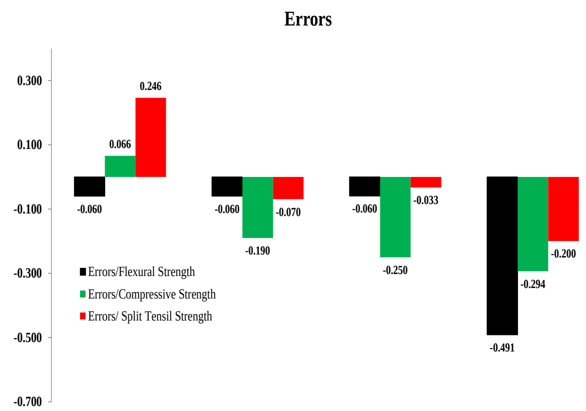

Fig. 10: The computational error of the ffb330 neural network.

The calculated errors between the outputs of the reference article and the values calculated by the selected neural network are presented in accordance with Figure 10 in the following.

4. Conclusion

In this study, the main purpose was to predict the strength parameters of a concrete sample containing additives using a neural network. Therefore, by doing trial and error, the most optimal neural network structure is selected, and the numerical values of flexural, compressive, and tensile strength predicted by the selected neural network are presented. After that, the difference between the calculated values and numerical output from the reference article [25] is compared. Therefore, based on the results of this study, it was observed that the structure of the neural network will have a significant impact on the accuracy of the prediction. According to the control criteria, such as executive performance and regression correlation coefficient, the most optimal neural network was obtained with three layers and 30 neurons in each layer. Thus, increasing the number of layers does not always increase the accuracy of the network. On the other hand, based on the results of this study, it was found that data normalization can optimally increase the accuracy of the neural network for predicting the desired parameters. The predicted values obtained from the residual analysis by the selected neural network (Ffb330), compared to the reference article, indicate a difference of 1.688% in flexural strength, 1.92% in compressive strength, and 0.21% in tensile strength. Thus, the use of the proposed neural network to estimate the strength parameters of concrete in comparison with experimental studies is considered as a desirable and quite cost-effective method in terms of economics and time.

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