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Neural prediction of mechanical properties of fiber-reinforced lightweight concrete containing silica fume and nano-silica

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Abstract. Experimenting to acquire the optimum result for producing a product in a real environment takes a long time and has various costs. Numerical simulations help save time and improve accuracy in implementing numerous complex tests. The present study exploits neural networks in MATLAB to calculate the mechanical properties of fiber-reinforced lightweight concrete under different fractions of silica fume and Nano silica, steel and polypropylene fibers, cement, and scoria. Concrete specimens were constructed under different mix designs and subjected to 7- and 28-day compressive, tensile, flexural, and initial and ultimate water absorption tests. Then, a multilayer perceptron (MLP) was used as the neural network. Furthermore, 70 % of the specimens were utilized as the training data samples, 15 % were exploited as the validation data samples, and the remaining 15 % were employed as the testing data samples. The MLP was trained for seven inputs, one hidden layer, and 20 neurons. The model training, testing, and overall accuracy were 100 %, 97.3 %, and 99.5 %, respectively, indicating the model is efficient and effective.

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1. *Introduction*

As the upper structures became lighter, the foundation volume and construction time will be reduced, leading to lower costs. By using natural or synthetic lightweight aggregates in the concrete, the concrete weight and thus, the foundation dimensions would be reduced, less bars would be needed, forming and bracing would cost less during section construction, better thermal isolation and sound absorption would be achieved, the transportation costs would decrease, the fire resistance would increase, and the freeze/thaw cycles would improve, compared to conventional concrete. Fiber-reinforced concrete can be used for a wide range of applications due to its high ductility, profound strength, high energy absorption capacity, and high cracking resistance.

Nowadays, technology has come to the aid of humans to perform their tasks faster, with higher accuracy and lower cost. Here, we intend to employ an artificial neural network (ANN) and experimental experience to take a step in that direction. ANN and experimental data are used in this study to predict the mechanical properties of lightweight fiber-reinforced concrete.

The use of lightweight concrete (LWC) has been a feature of construction for the past several decades. LWC has higher seismic resistance particularly for buildings located in the seismic regions. A recent study in Iran shows that destruction of most buildings is due to great inertial force and lack of structural tolerance for the load [1]. Therefore, lightweight concrete is employed in light of its unique properties in several applications, including high-rise structures, large multi-span bridges, and buried military structures for energy absorption and dissipation [2]. Lightweight concrete can be fabricated using various methods, including removing fine-grained aggregates and creating air bubbles through chemical foam admixtures. Lightweight aggregates (LWAs) are the most common method of fabricating lightweight concrete [3, 4]. Scoria is a porous igneous rock with an edged appearance resulting from volcano eruptions and rapid cooling in the air, typically appearing in red to brown [5]. Structural lightweight aggregate concrete [SLWAC] criterion of ACI standard requires a 28-day cylinder compressive strength of 17 MPa and air-dry unit weight of less than 1840 kg/m^3. However, maximum unit weight of SLWC in some European standards such as DIN-4219, PN-91, ENV92 is defined as 2000 kg/m^3 and in PREN 206 is taken to be 2100 kg/m^3 (Euro light concrete 1998) [6]. Silica fume (also known as micro-silica) is an amorphous micro-scaled material, which improves the stability and strength of concrete. Shannag [7] demonstrated that the addition of silica fume at a fraction of 15 % enhanced concrete strength. Moreover, nanosilica may react with $Ca(OH)_2$ crystals and produce the calcium silicate hydrate (C-S-H) gel, increasing the early strength of hardened cement paste and concrete [8]. Qing et al. [9] compared nanosilica to silica fume in strength enhancement and reported that nanosilica had much higher pozzolanic activity than silica fume at early ages. Li [10] showed that a small fraction of nanosilica enhanced concrete compressive and flexural (bending) strengths and abrasion resistance. Ji et al. [11] found that the simultaneous use of silica fume and steel fibers enhanced the concrete compressive strength. Gesog˘lu et al. [12] concluded that the combined effect of SF and steel fibers may increase the compressive strength. Mahoutiyan et al. [13] studied the effects of steel and polypropylene fibers on concrete and found that polypropylene fibers had lower contributions than steel fibers to compressive strength enhancement. Hajmohammadi Baghba et al. [14] evaluated the effects of polypropylene fibers on self-compacting concrete (SCC) with recycled aggregates and reported a rise in polypropylene fibers enhanced impact strength, tensile strength, and energy absorption. In addition, soft computing can be employed to accurately predict the strength of asphalt mixtures. Accordingly, Zehtabchi et al. [15] employed fuzzy logic and predicted the marshal stability of polymer-modified asphalt mixtures with an error below 5 %. The type, quality, and amount of materials in concrete fabrication strongly influence its compressive strength. For example, the water-cement ratio and chemical and/or mineral admixture types and fractions are influential parameters. Since these parameters can cover relatively wide ranges, it is difficult to predict the concrete behavior. Therefore, advanced modeling is required to cope with this challenge. Artificial neural network (ANN) models are efficient instruments inspired by the biological neural network as a complex nonlinear regression model for minimizing the cost of predicting concrete behavior. Computers have enabled computational algorithms in the past several decades. Numerous studies have been conducted by computer scientists, engineers, and mathematicians on the computational behavior simulation of the human brain, which are classified into artificial intelligence (AI) and ANN sub-branch. Ruslan Ibragimov et al. [16] conducted a case study on construction material titled "The effect of metal and polypropylene fiber on technological and physical-mechanical properties of activated cement compositions" to study the effect of the fiber of various materials and sizes on the rheological properties of concrete mixtures and the physical and mechanical properties of self-compacting concrete and mortar obtained by the activation of Portland cement in the vortex layer device. According to the results, the metal fiber increases the shear stress of the concrete mixture obtained from activation by 1.56 times, which is higher than the polypropylene fiber (up to 1.34 times). In addition, Polypropylene fiber increases the crack resistance by 1.57 times, but metal fiber increases the impact strength of fine-grained concrete by 2.6 times. Oguzhan Yavuz Bayraktar et al. [17] studied the impact of recycled coarse aggregate (RCA) and fly ash (FA) on the mechanical properties and durability of polypropylene fiber-reinforced concrete exposed to freeze-thaw cycles and MgSO4 with artificial neural network (ANN) modeling experimentally. It was found that the combined use of 50 % RCA and PPF exhibited the best performance in terms of abrasion resistance. The principal result of this study is that using RCA, FA, and PPF in concrete can provide better mechanical and durability performance compared to conventional concrete. They also suggested that mixing ratios of concretes with RCA, FA, and PPF could be reliably determined by using Bayesian regularized ANN models. Based on this model, the mixing ratios of concrete can be determined based on the desired properties. Alaa M. Morsy et al. [18] conducted a case study named "predicting mechanical properties of engineering cementitious composite reinforced with PVA using artificial neural network". They designed an artificial neural network (ANN) to predict the mechanical properties of engineered cement composites (ECC), such as compressive strength, flexural strength, and direct tensile stress-strain curve. The used data set was 151, 76, and 44 test results for compressive strength, flexural strength, and direct tensile stress-train curve collected from recently published research. Based on the results, which include regression of all data, 98.4 % for compressive strength, 97.7 % for compressive strength, 98.4 % for tensile strength, relative minimum error of (0.15:9.40٪) for compressive strength, (0.05:4.71٪) for flexural strength, and (1.40:5.00٪) for tensile strength, the artificial neural network can predict these parameters with great proximity. Al-Shiri et al. [19] evaluated the strength of lightweight concrete in a structure using neural networks. They used lightweight expanded clay aggregate (LECA) to reduce the weight of the concrete. The experiments were conducted for 3, 7, 14, and 28-day specimens, and they were able to provide a good approximation of lightweight concrete strength using sand, water/cement ratio, lightweight fine aggregate, lightweight coarse aggregate, silica fume used in solution, silica fume used in addition to cement, superplasticizer, and curing period as the input. They employed one input layer, two hidden layers, and one output layer for their network. The hidden layers are composed of 14 and 6 neurons, sequentially, and the output layer is composed of four neurons. The neural network prediction results indicate that the experimental data were measured and estimated by the network with an appropriate accuracy. Alton and his colleagues [20] used a neural network to estimate the strength of the steel fiber-contained lightweight concrete. A total of 126 specimens of 150×300 mm were made in the laboratory. The input parameters of the neural network were steel fibers, water, water/cement ratio, sand, and superplasticizer. They used multilayer perceptron neural network (MLP) in their study. They also used multiple linear regression (MLR) method, a statistical technique to estimate data, to compare the results with MLP. The algorithm used in this experiment is the Levenberg-Marquardt algorithm (LM). The results showed that the neural network offered a good estimation of the data. In case of better neural network training, the results could even improve in their estimation. Regarding the high correlation coefficient and the diversity of parameters, it can be expected that the neural network can offer a wider range of solutions than complex statistical techniques. In a research, Saudi and his colleagues [21] tried to predict the creep deformation of asphalts modified with polymer, using an artificial neural network. They suggested that a proper neural network architecture with an error correction approach can predict the output parameter (i.e., creep rate) with a small error using various input parameters (e.g., temperature, rubber contents, loading stress, and compactness). Abdullah [22] studied the application of artificial neural networks to predict concrete properties. The selected network input parameters are water/cement ratio, aggregate/cement ratio, and slump values. According to the results, the average absolute error (AAE) value was found to be less than 3.46 % for the proposed model and the NRMSE value was the lowest 0.0011, indicating that artificial neural networks are an invaluable modeling technique. In a research, Ofrikhter and his colleagues [23] employed artificial neural networks to estimate the mechanical parameters of soils based on known physical characteristics. As a result of this research, an artificial neural network has been obtained that makes it possible to predict the angle of friction and the specific cohesion of clay soils with reasonable accuracy.

ANNs were proposed by Yang (1903) [24]. The inception of artificial neurons can be traced back to 1943 when Warren McCulloch, a neuroscientist, and Walter Pitts, a mathematician, put forth a model of a neuron in their article entitled "A Logical Calculus of Ideas Immanent in Nervous Activity." Their proposed model was a simplistic computational framework grounded on propositional logic that offered a blueprint for how neurons operate to accomplish intricate tasks. Their work demonstrated that a network of neurons has the capability to compute any mathematical or logical function [25]. The initial scientific application of neural networks began to take shape during the latter part of the 1950s. In this epoch, Frank Rosenblatt formulated the concept of perceptron networks and their associated learning rules. In 1957, Rosenblatt introduced an algorithm that initializes parameter values and subsequently updates them toward optimal parameters by analyzing distinct input values. Moreover, Rosenblatt and his colleagues conducted experiments that showed that perceptron networks have the ability to recognize patterns. In essence, perceptron acquire a set of input signals and if their linear combination surpasses a predetermined threshold value, the perceptron becomes activated, while if it falls below this value, the perceptron remains deactivated [26]. Civil engineers started using ANNs in 1990. Rajasekaran et al. [27] published papers on utilizing fuzzy neural networks in civil engineering. Lai et al. [28] estimated the concrete compressive strength using neural networks in 1996. Basma et al. [29] and Oh et al. [30] employed backpropagation neural networks to estimate the mix design of typical concrete and the cement hydration degree. Mousavinejad et al. [31] explored the effects of micro-silica (MS) and Nano silica on the mechanical properties of fiber-reinforced lightweight concrete. The present study used the data of Mousavinejad et al. [31], as reported in Tables 1 and 2.

The main objective of this study is to evaluate the performance of the artificial neural network (ANN) approach to predict the mechanical properties of lightweight fiber-reinforced concrete with adequate precision. The ANN was composed of 7 input layers and 1 hidden layer, and it was trained using 20 neurons. The estimations were reasonably accurate, indicating the proper efficiency and accuracy of the chosen network.

2. Methods

2.1. Mix designs and specimen fabrication

Initially, a water-cement ratio of 0.3 was applied to all the specimens, with 10% and 15% silica fume fractions. Then, hooked steel (50 mm) and polypropylene (12 mm) fibers were used, and some water was mixed with dry LWAs for 30 min pre-wetting to fabricate the specimens. In the following procedure, sand was added and mixed with LWAs before adding cement. Finally, water and the superplasticizer were added to the mixture. The concretes were molded and cured in the laboratory at 20–25 °C for 24 h. Table 1 shows the mix designs [31].

Table 1. Mix designs [31].

Specimen	Cement	Silica Fume	Nano silica	Water	Sand	Scoria	Superplasticizer	Polypropylene Fiber	Steel Fiber
Control	500	0	0	150	705	676	2.5	0	0
MS 10	450	50	0	150	705	661	4	0	0
MS10 PP2	450	50	0	150	705	657	4	1.8	0
MS10 PP2 S4	450	50	0	150	705	649	5	1.8	31.4
MS10 PP2 S8	450	50	0	150	705	641	6	1.8	62.8
MS 15	425	75	0	150	705	653	5	0	0
MS15 PP2	425	75	0	150	705	650	5	1.8	0
MS15 PP2 S4	425	75	0	150	705	641	6	1.8	31.4
MS15 PP2 S8	425	75	0	150	705	633	7	1.8	62.8
MS10 Na3	435	50	15	150	705	646	5	0	0
MS10 Na3 PP2	435	50	15	150	705	643	5	1.8	0
MS10 Na3 PP2 S4	435	50	15	150	705	635	6	1.8	31.4
MS10 Na3 PP2 S8	435	50	15	150	705	627	7	1.8	62.8
MS10 Na5	425	50	25	150	705	638	5	0	0
MS10 Na5 PP2	425	50	25	150	705	635	5	1.8	0
MS10 Na5 PP2 S4	425	50	25	150	705	627	6	1.8	31.4
MS10 Na5 PP2 S8	425	50	25	150	705	618	7	1.8	62.8

Table 2. Compressive, flexural, and tensile strengths and water absorption [31].

Specimen	7-Day Compressive Strength (MPa)	28-Day Compressive Strength (MPa)	Initial Water Absorption (%)	Ultimate Water Absorption (%)	Tensile Strength (MPa)	Flexural Strength (MPa)
Control	19	22	2.21	3.89	2.49	3.78
MS 10	24	29	1.58	2.31	3.11	4.8
MS10 PP2	23	27.8	1.62	2.37	3.3	5.28
MS10 PP2 S4	26	31.3	1.77	2.51	3.72	6.06
MS10 PP2 S8	25.8	32	1.89	2.65	3.97	6.66
MS 15	22.5	26.5	1.79	2.66	2.79	4.44
MS15 PP2	21.2	25.8	1.84	2.74	2.98	4.74
MS15 PP2 S4	23.8	28.5	1.97	2.82	3.16	5.58
MS15 PP2 S8	25	29	2.09	2.98	3.41	6.06
MS10 Na3	26.8	31.5	1.42	1.95	3.31	5.16
MS10 Na3 PP2	25.5	30	1.44	2	3.57	5.64
MS10 Na3 PP2 S4	28.8	34	1.58	2.11	3.85	6.78
MS10 Na3 PP2 S8	29	35	1.76	2.3	4.08	7.26
MS10 Na5	24.5	28	1.74	2.53	2.88	4.56
MS10 Na5 PP2	23.2	27	1.75	2.62	3.07	4.92
MS10 Na5 PP2 S4	26	30	1.91	2.78	3.41	6.12
MS10 Na5 PP2 S8	26.5	30.8	2.02	2.83	3.62	6.48

2.2. Artificial Neural Network (ANN)

ANNs consist of simple parallel operation elements inspired by the biological neural system. Neural Networks function is determined through the connection of elements in nature. Therefore, it is possible to construct an artificial structure based on natural networks where the connections are weighted to determine the relationships of its elements. A multilayer perceptron (MLP) is a basic neural network model that simulates the transmission process of the human brain and focuses on the network behavior and signal propagation of the human brain. Therefore, MLPs are sometimes known as feedforward ANNs since two or more neurons can be combined into a layer. A neural network may consist of several layers with a unique weight matrix, bias vector, and output. The layers positioned between the input and output layers are the hidden layers. Fig. 1 depicts a schematic of a feedforward ANN.

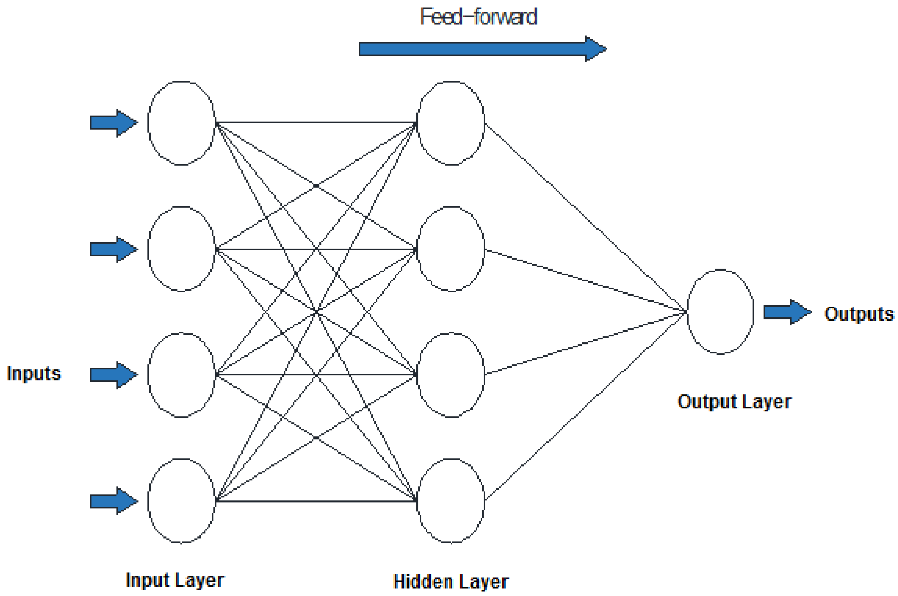

Figure 1. Schematic of a feedforward ANN.

2.3. Model description and training

2.3.1. Dataset

An efficient ANN requires sufficient and detailed data of the critical parameters. Thus, the present study employed 17 experimental concrete specimens of various mix designs. The cement, Silica Fume, Nano-silica, scoria, superplasticizer, and polypropylene and steel fiber quantities were used as the inputs, whereas the 7- and 28-day compressive strength, initial and ultimate water absorptions, tensile strength, and flexural strength were assumed to be the outputs (Table 1 and Table 2).

An ANN seeks to learn through variations in the weights and biases performed via iterations. In other words, a training dataset is introduced several times to the algorithm, which recognizes differences in the training data by changing the weights and deviations. Backpropagation is one of the most commonly used iteration approaches in neural networks consisting of feedforward and backpropagation stages. The input data are multiplied by the corresponding weights and summed up with the biases. Then, the output, which is likely to differ from the actual output, is obtained to calculate the error in the first iteration. Once the error has been found through the weights and deviations, the algorithm moves to the second stage in one iteration, updating the weights and biases to diminish the error in the next iteration. These iterations continue until the output approaches the actual output for all the training data.

2.3.2. Optimal ANN structure

The networks with two hidden sigmoid and linear output neurons were investigated to identify the optimal ANN topology. The performance of ANNs was evaluated for different numbers of neurons, and the numbers of neurons were set based on trial and error. This study adopted the root-mean-square error $(RMSD)$ as the evaluation criterion, which is calculated as:

$$RMSD = \sqrt{\frac{\sum_{i=1}^{N}\left(X_i - \bar{X}\right)}{N}}, \qquad (1)$$

where X_i presents the actual data point, $\bar{X}$ represents the estimated data point, and N denotes the number of data points.

The MLP model with seven inputs, one hidden layer, and 20 neurons was trained, as shown in Fig. 2.

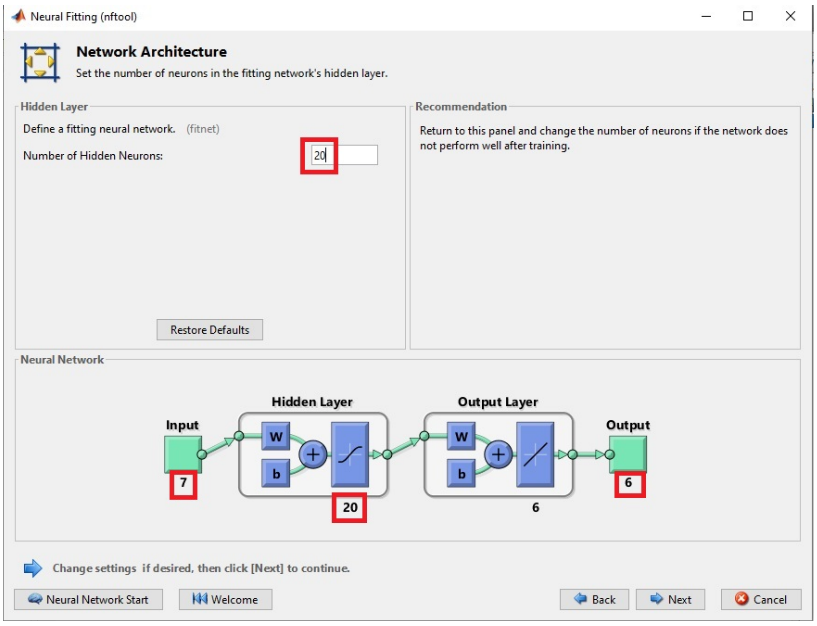

Figure 2. MLP architecture with inputs, output, and neurons in MATLAB.

Bayesian neural networks are a method based on neural networks in modeling nonlinear and complicated problems through specific algorithms and statistical methods. It can be used to model cause and effect relationships of a process, analyze the circumstance, and predict the future status of a system. Bayesian regularization was used to train the MLP model and determine the coefficients. Furthermore, the data were divided into training (70 %), validation (15 %), and testing (15 %) dataset, respectively. Table 3 summarizes the ANN parameters.

Table 3. ANN parameters.

ANN	MLP
Type	Feedforward
Training algorithm	TRAINLM
Error algorithm	Backpropagation
Optimization function	Bayesian regularization
Training data	70 %
Validation data	15 %
Testing data	15 %

3. Results and Discussion

The correlation coefficient R was used for evaluating the model. The optimized trained model accurately predicted the 7- and 28-day compressive strengths, flexural strength, tensile strength, and initial and ultimate absorptions. In this context, testing (simulation) was carried out on 3 data never used in ANN. From these results, the model yields sufficient reliability as the training regression was 100 %, testing regression was 97.3 % and all data regression was 99.5 %. Fig. 3 compares the actual and predicted regression values of the training, validation, and testing datasets. As can be seen, the model was found to have high performance.

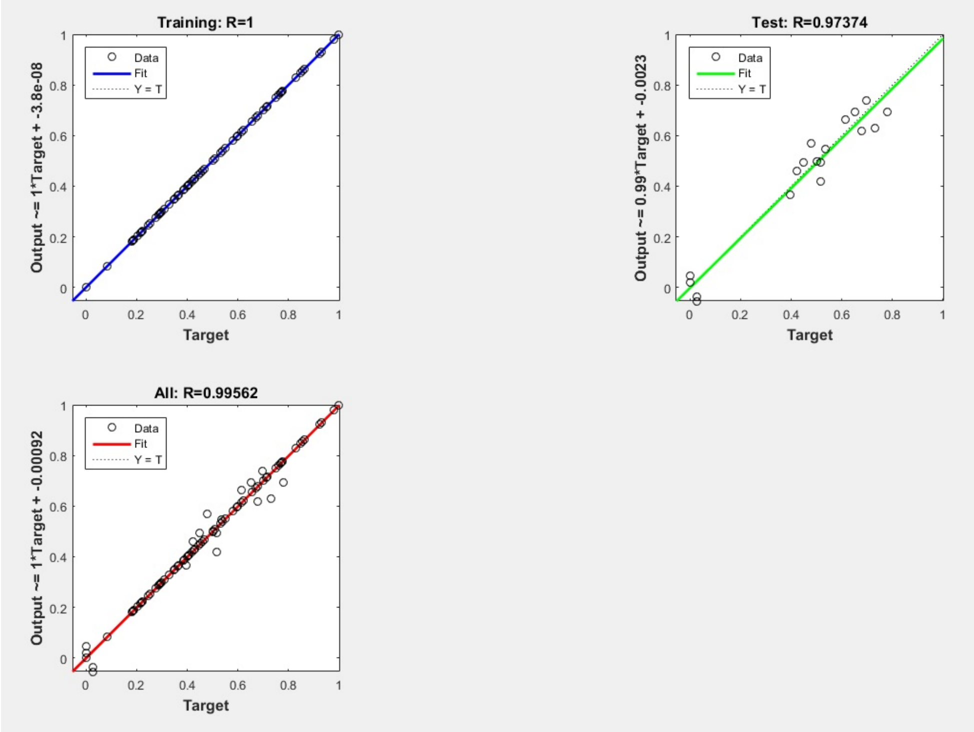

Figure 3. Actual versus predicted regressions for the training, validation, and testing datasets.

The data (Table 1and Table 2) were normalized and introduced to the model as:

$$Z = \frac{X - \min(x)}{\max(x) - \min(x)}, \tag{2}$$

where x is the input values of Table 1 and Table 2. Thus, the normalized outputs should be decoded and compared to the actual values in Table 2 using Eq. (2). Table 4 provides the decoded outputs.

Table 4. MLP predictions.

Specimen	7-Day Compressive Strength (MPa)	28-Day Compressive Strength (MPa)	Initial Water Absorption (%)	Ultimate Water Absorption (%)	Tensile Strength (MPa)	Flexural Strength (MPa)
Control	19.00	22.00	2.21	3.89	2.49	3.78
MS 10	24.00	29.00	1.58	2.35	3.11	4.80
MS10 PP2	23.00	27.80	1.62	2.41	3.30	5.28
MS10 PP2 S4	26.00	31.30	1.77	2.55	3.72	6.06
MS10 PP2 S8	25.80	32.00	1.89	2.68	3.97	6.66
MS 15	22.50	26.50	1.79	2.69	2.79	4.44
MS15 PP2	21.20	25.80	1.84	2.77	2.98	4.74
MS15 PP2 S4	23.80	28.50	1.97	2.85	3.16	5.58
MS15 PP2 S8	25.00	29.00	2.09	3.00	3.41	6.06
MS10 Na3	26.80	31.50	1.42	2.00	3.31	5.16
MS10 Na3 PP2	25.50	30.00	1.44	2.05	3.57	5.64
MS10 Na3 PP2 S4	27.85	32.43	1.60	2.16	3.89	6.47
MS10 Na3 PP2 S8	29.00	35.00	1.76	2.34	4.08	7.26
MS10 Na5	25.19	29.09	1.71	2.56	2.85	4.52
MS10 Na5 PP2	23.20	27.00	1.75	2.65	3.07	4.92
MS10 Na5 PP2 S4	24.72	27.95	1.87	2.71	3.40	5.64
MS10 Na5 PP2 S8	26.50	30.80	2.02	2.86	3.62	6.48

The differences between the experimental and numerical were measured to evaluate model performance further (Table 5). According to Table 5, the differences were minimal, suggesting that the proposed model had an excellent and reliable performance.

Table 5. Differences between the experimental and numerical quantities.

Specimen	7-Day Compressive Strength (%)	28-Day Compressive Strength (%)	Initial Water Absorption (%)	Ultimate Water Absorption (%)	Tensile Strength (%)	Flexural Strength (%)
Control	0.00	0.00	0.00	0.00	0.00	0.00
MS 10	0.00	0.00	0.00	–1.76	0.00	0.00
MS10 PP2	0.00	0.00	0.00	–1.65	0.00	0.00
MS10 PP2 S4	0.00	0.00	0.00	–1.42	0.00	0.00
MS10 PP2 S8	0.00	0.00	0.00	–1.21	0.00	0.00
MS 15	0.00	0.00	0.00	–1.19	0.00	0.00
MS15 PP2	0.00	0.00	0.00	–1.08	0.00	0.00
MS15 PP2 S4	0.00	0.00	0.00	–0.98	0.00	0.00
MS15 PP2 S8	0.00	0.00	0.00	–0.79	0.00	0.00
MS10 Na3	0.00	0.00	0.00	–2.56	0.00	0.00
MS10 Na3 PP2	0.00	0.00	0.00	–2.44	0.00	0.00
MS10 Na3 PP2 S4	3.28	4.62	–0.98	–2.50	–1.05	4.55
MS10 Na3 PP2 S8	0.00	0.00	0.00	–1.78	0.00	0.00
MS10 Na5	–2.81	–3.88	1.68	–1.29	1.09	0.96
MS10 Na5 PP2	0.00	0.00	0.00	–1.25	0.00	0.00
MS10 Na5 PP2 S4	4.94	6.82	2.17	2.41	0.26	7.82
MS10 Na5 PP2 S8	0.00	0.00	0.00	–0.97	0.00	0.00

Fig. 4 compares the model outputs to the actual values. As can be seen, the estimates and actual values were in good agreement, suggesting that the proposed ANN is efficient and effective.

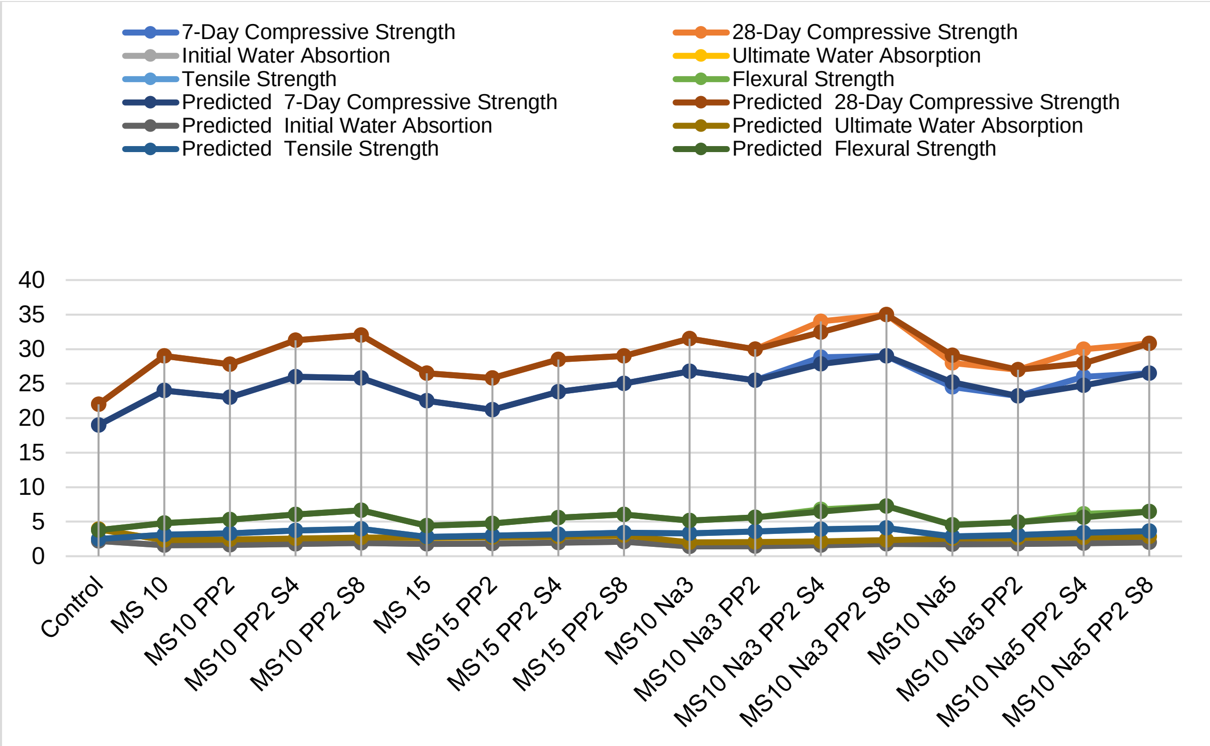

Figure 4. Comparison of experimental and numerical quantities.

4. Conclusion

(1) This study employed an ANN model to estimate the mechanical properties of fiber-reinforced lightweight concretes containing silica fume (MS) and Nano silica.

(2) The inputs included the fractions of cement, Silica Fume, Nano-silica, scoria, superplasticizer, and polypropylene and steel fibers, whereas the outputs involved the 7- and 28-day compressive strengths, initial water absorption, ultimate water absorption, tensile strength, and flexural strength. The experimental data of 17 concrete specimens were adopted from.

(3) Using an ANN requires determining the optimal number of hidden layers and neurons in a trial-and-error process to obtain the most accurate outputs.

(4) Although the predictive performance of an ANN model is limited to the training data, the model can be re-trained using new training algorithms to cover a broader range of inputs.

(5) The model estimates were in good agreement with the experimental data, suggesting that the model was efficient and produced reliable outputs.

(6) The maximum error was calculated as much as 4.94 %, 6.82 %, 2.17 %, 2.56 %, 1.09 %, and 7.82 % for the 7-day compressive strength, 28-day compressive strength, initial water absorption, ultimate water absorption, tensile strength, and flexural strength, respectively.

(7) Future studies are suggested to evaluate different coarse- and fine-grained aggregates and reinforcement fibers and incorporate a more significant number of specimens to obtain more comprehensive results. Furthermore, using recycled aggregates, e.g., rubber and asphalt aggregates in concrete fabrication is crucial to avoid environmental degradation.

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