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Prediction of Shear Strength of Concrete using the Artificial Neural Network

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ABSTRACT

Artificial neural networks (ANN) are known to be increasingly popular and used in several engineering applications, such as in the civil engineering field. In this study, this method was used to develop an optimal model to predict the shear strength of concrete using the experimental data sets. All the data sets were trained and tested using ANN to obtain the prediction of the shear strength of concrete material. The model ANN was trained and tested using test data sets obtained from 51 concrete mixes from previous experimental data sets. 33 (65%) concrete mixes data sets were chosen randomly and used as input for training. The remaining 18 (35%) mixes data were divided equally into testing and validation data sets. Feed-forward backpropagation was chosen for the neural network design and Levenberg-Marquardt was used as the learning algorithm. An S-shaped sigmoid function was used to predict the probability as output between the range 0 to 1. Ten different types of architecture networks with different types of structures and neurons number were used to obtain the best model. The optimal ANN architecture (33-10-1) was found to have the highest correlation coefficient (R) of 0.99888 and the lowest mean square error (MSE) 0.00085. The shear strength based on the ANN model perfectly matched the values of the experimental data sets.

Keywords: *optimal network, shear strength, artificial neural network, prediction model, activation function*

1. INTRODUCTION

In today's construction industry, concrete is the most commonly used composite building material. Given rapid economic growth and urbanization, the use of concrete materials is increasing due to the accessibility of its various components, flexibility, durability, and suitability [1]. The concrete matrix is composed of chemically inert materials such as fine and coarse aggregates, and the binder, usually cement, serves as an adhesive that holds the concrete matrix together when mixed with water. The shear strength behavior and strength of structural members in design are of critical importance in structural design. There are numerous ways in which concrete components can fail. Due to the brittle nature of concrete structures, shear failure is one of the most common and worst failure modes [2].

Shear structural problems in concrete structures are much riskier than flexural structures because shear failures can occur without notice and without the ability to redistribute internal forces. The shear strength of concrete is known as its ability to resist a force that would cause one member to slide over another on the internal plane without failing. Each concrete element affects the properties of the concrete and must be controlled in terms of composition and

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quantity if the result is to be consistent, workable, and of adequate strength. According to [3], the proportion of concrete mix is the amount of material required in the production of concrete for a specific purpose. To obtain more accurate data and to evaluate the shear strength of concrete, shear strength results must be numerous and comparable with one another.

Many tests and research approaches have been developed to estimate the strength of a particular mix ratio more quickly. To predict the strength of concrete, various machine learning algorithms are used. According to [4], machine learning is the study of how machines can be used to mimic human learning activities, learn new information and skills, and recognize existing knowledge. It can be seen in [5] where he has conducted a study to formulate the shear strength of reinforced concrete shear walls by artificial intelligence-based algorithms such as Artificial Neural Networks (ANN), Neural Network-Based Group Method of Data Handling (GMDH-NN), and Genetic Algorithms (GEP). Meanwhile, [6-8] uses machine learning algorithms in ANN modeling to predict the shear strength of the deep beam, reinforced concrete, and fibre reinforcement bar concrete beams. Besides that [9] has applied Bayesian learning to train a multi layer perceptron network on an experimental test on Reinforced Concrete (RC) beams without stirrups failing in shear. [10] in his work was using bat-algorithm-based Artificial Neural Network to predict the shear strength of Fibre Reinforced Polymer concrete.

Machine learning approaches have been successfully employed to model the highly non-linear shear resistance in steel fiber reinforced concrete (SFRC) beams. In this regard, Nonlinear Regression Algorithm (NRA), Surface Response Methodology (SRM), and the artificial neural network (ANN) were recently applied to predict the shear resistance concrete structure. NRA is considered an important tool that can model the complex process in various engineering disciplines. However, the proposed model predicting shear resistance based on NRA is less accurate than the ANN.

Artificial intelligence is used to study the mechanical properties of concrete mix, including shear strength, compressive strength, and tensile strength [1]. Some studies anticipate the mechanical properties of concrete mixes, such as compressive strength, but now researchers have conducted studies on the shear strength of concrete based on the concrete mix. For this study, the artificial neural network model (ANN) was used to obtain a more suitable and more convenient method to predict the shear strength of concrete material. A variety of civil engineering, geotechnical, and management problems have been effectively implemented by various studies [11]. The shear strength of concrete as output is calculated by the model ANN by inputting the mixed proportions of concrete materials into the computer.

The objective of this study is to determine the optimum model of ANN by finding the highest value of correlation coefficient R and the lowest mean square error (MSE). The best model of ANN to predict the exact value of shear strength by varying the output is also investigated.

2 MATERIALS AND METHODS

2.1 Artificial Neural Network (ANN)

ANN is an artificial intelligence technology that is widely used to model complicated systems that are difficult to represent using traditional modeling approaches such as mathematical

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modeling. According to [12], neural networks were inspired by the biological neural networks that make up the brain, which is highly nonlinear and complex. It can arrange its structural components (neurons) in such a way that it can perform certain computations (such as motor perception and control) much faster than today's fastest digital computers.

Neural networks replicate the biological network of the central nervous system of nerve cells (neurons). Artificial neurons, sometimes called units or nodes, require many input connections with a specific weighting. This unit determines the number of weighted inputs and the activation function applied. The output is sent through the output connection [1].

The input layer, one or more hidden layers, and the output layer are the three layers of neurons that make up an ANN. Weight, transport function, and bias connect all hidden layers, but there is no connection between nodes on the same layer.

Typically, neural networks are adapted or trained to produce specific target outputs in response to specific inputs. The network is modified in response to the output and target comparison until the network output matches the target. To continue the group training of the network, the weights and biases are changed depending on the total set (batch) of input vectors. After each input vector is displayed, further training is required to adjust the weights and bias of the network.

Neurons in the hidden layer, as shown in Figure 1, are connected by network weights, *w*, and bias, *b* with the previous and subsequent layers. There are two main architectures of the neural network: forward and backpropagation.

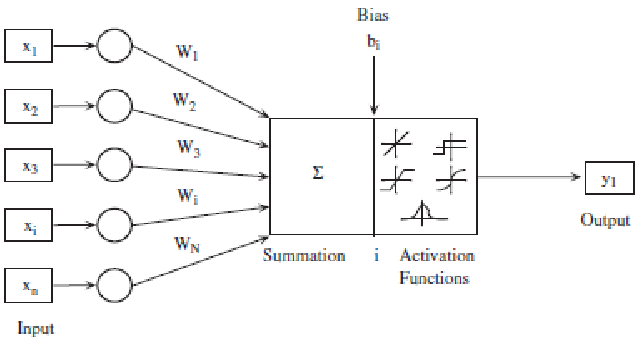

Figure 1: Artificial Neuron Model [2].

Feed Forward Neural Networks is the type of neural networks information that flows in only one direction for example from the input layer to the output layer. When the weights are once decided, they are not usually changed. One either explicitly decides weights or uses functions like Radial Basis Function to decide weights. The nodes here do their job without being aware whether the results produced are accurate or not, for example they do not re-adjust according to the result produced. There is no communication back from the layers ahead.

Whereas Back-Propagation Neural Network is where the information passes from the input layer to the output layer to produce a result. Error in the result is then communicated back to previous layers. Nodes get to know how much they contributed to the answer being wrong. Weights are re-adjusted then the neural network is improved and it learns. There is a bi-

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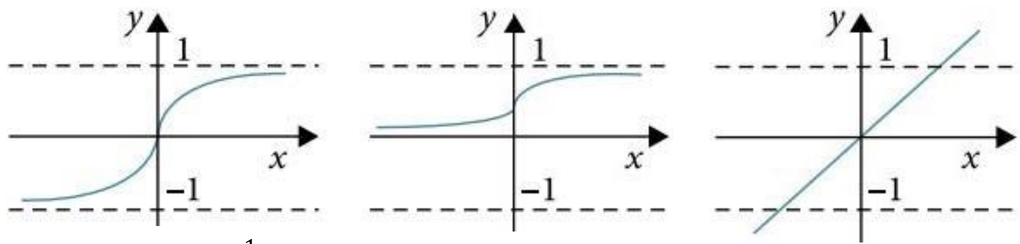
directional flow of information. This has both algorithms implemented, feed-forward and back-propagation.

ANN training could be supervised or unsupervised [13]. Multilayer feed-forward is used for backpropagation in engineering applications. The network input is connected to the first hidden layer of each neuron whereas the last hidden layer of the network input. Calculation of the output of neuron:

$$y = f(\sum(i_1 * w_1) + b) \tag{1}$$

where y is the neuron output, i is the previous layer neuron input, w is the neuron weight, b is the bias threshold modeling and f is the activation function [13].

The activation function is a function in neural networks that defines the output activity of neurons. The common activation function of a backpropagation neural network such as logsig, tansig and purelin are shown in Figure 2.



$y = logsig(x) = \frac{1}{1+e^{-x}}$ $\quad$ $y = tansig(x) = \frac{2}{1+e^{-2x}} - 1$ $\quad$ $y = purelin(x) = x$

Figure 2: Different Types of Transfer Functions used in ANN [14]

2.2 Development of ANN Model

This study collected all the data from previous experiments from 16 different authors [15-30] and stored it in the MATLAB workspace as input data sets. The neural network model was developed using MATLAB (R2020a). The selection of the most appropriate network topology, the number of hidden layers, and the number of neurons in each hidden layer were determined by trial and error.

The network architecture in this study was designed by using one hidden layer, two hidden layers, and networks with various activation functions. The topology of the concrete mix design model was determined by trial and error. Figure 3 illustrates the example architecture of the model for solid concrete. The concrete property models created include three layers: an input layer with thirty-three neurons, a hidden layer with ten neurons (Figure 3(a)) and two hidden layers with five neurons and four neurons in hidden layer 1 and hidden layer 2, and an output layer with one neuron (Figure 3(b)).

The type feedforward neural network (FNN) or Feed-forward backpropagation was chosen for the neural network design. To improve the network prediction performance, neural network architectures of 33-10-1 and 33-5- 4-1 were chosen by using a multilayer feed-forward backpropagation network. The selection of the proposed ANN architecture was mainly

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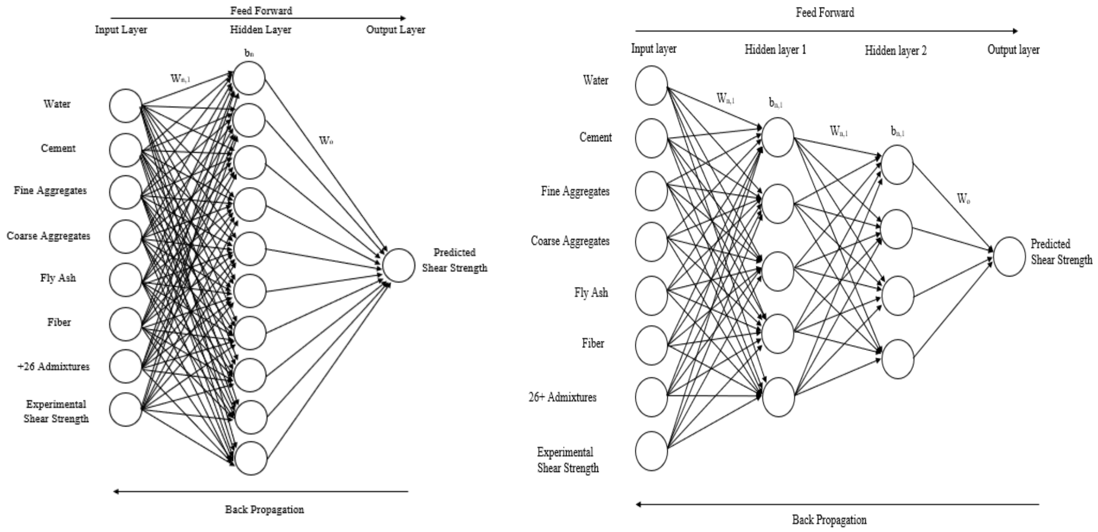
performed based on a trial-and-error approach, whereby the number of hidden layers and its neuron number were chosen and its training performance was monitored by the mean square error during the training phase using the Levenberg-Marquart algorithm.



a) Structure 33-10-1 b) Structure 33-5-4-1

Figure 3: Schematic of the ANN Structur

2.3 Experimental Datasets Acquisition

One of the most important components for the successful execution of an ANN model is the data sets that are essential for ANN model learning. As mentioned earlier, ANN models are trained using data collected in previous experimental tests. A total of 51 experimental data sets with a total of 33 input nodes were used as input variables with a size of (51 x 1) to predict the shear strength of concrete as an output variable as listed in Table 1. The parameters of the data started with the minimum value and ended with the maximum value.

Table 1: Ranges of Parameters for Datasets

Parameter	Unit	Min	Max
Water, W	(kg/m^3)	25.6	387
Cement, C	(kg/m^3)	0	480
Fine Aggregates, FA	(kg/m^3)	0	1021.90
Coarse Aggregates, CA	(kg/m^3)	0	1816
Recycled Aggregates, RA	(kg/m^3)	0	985
GGBS	(kg/m^3)	0	1004
AE	(kg/m^3)	0	0.62
HRWR	(kg/m^3)	0	6.10
Super Plasticizer, SP	(kg/m^3)	0	3.33
Fiber, F	(kg/m^3)	0	234

Parameter	Unit	Min	Max
Fly Ash, FAsh	(kg/m^3)	0	727
Sodium Hydroxide, SH	(kg/m^3)	0	41
Sodium Silicate, SC	(kg/m^3)	0	171
Glenium, G	(kg/m^3)	0	1.75
Rheomac, R	(kg/m^3)	0	2.34
Water Reducer, WR	(kg/m^3)	0	4.64
Admixture, A	(kg/m^3)	0	30
Coal Ash, CAsh	(kg/m^3)	0	70
Binder GGBFS, BGGBFS	(kg/m^3)	0	680
Binder Fine Quartz,	(kg/m^3)	0	120

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Parameter	Unit	Min	Max
BFQ			
Slag Sand, SS	(kg/m^3)	0	511
Quartz Sand, QS	(kg/m^3)	0	171
EAF Slag Coarse, EAF	(kg/m^3)	0	489
NaOH Flakes, NaOH	(kg/m^3)	0	40
Sodium Phosphate, SP	(kg/m^3)	0	8
SAP	(kg/m^3)	0	4.464
Internal Curing, IC	(kg/m^3)	0	111.6

Parameter	Unit	Min	Max
Limestone Filler, LF	(kg/m^3)	0	88
Gypsum, GM	(kg/m^3)	0	9
Calcium Hydroxide, CH	(kg/m^3)	0	23
No. of Rebar, RC		0	10
Size of Rebar, D	(mm)	0	10
Experimental Shear Strength, VC	(MPa)	0.82	12.5

2.4 Determine the Lowest MSE

The experimental data sets were randomly chosen and divided into three subgroups: training set, test set, and validation set. With the number of data available, the data then were divided about 65% into training data sets and the remaining 35% were divided equally into test and validation data sets as suggested [31-34]. TRAINLM or Levenberg-Marquardt backpropagation, is the learning function used in this work to make the training faster with a higher performance [35,36]. In construction, backpropagation is highly recommended, extremely fast, has a large memory compared to other training functions, and is the most successful and widely used method. Backpropagation algorithms are supervised learning algorithms. In this study, an S-shaped sigmoid function was selected due to the capability of this function to predict the probability as output between the range 0 to 1 [37-39]. The data also has been normalized to (-1,1).

After the network training is complete, the results are compared to find the optimal ANN model. The performance metrics to measure the optimality were based on the correlation coefficient R, mean square error (MSE). In addition, when training the neural networks at hand, the MSE was used to evaluate the network performance. The better the prediction, the closer the MSE value is to zero [40].

$$MSE = \frac{\sum_{i-1}^{n}\sum_{j=1}^{m}(y_{ij} - t_{ij})^2}{n} \tag{2}$$

Equation (2) is used to define MSE, where *n* is the number of patterns in the validation set, *m* is the number of components in the output vector, *y* is the output of a single neuron, *j*, vector, *i* denotes each input pattern.

3. RESULT AND DISCUSSION

3.1 Determining the Optimal network

The results of each training session were recorded, and performance was evaluated and compared using R values and MSE. To achieve effective and acceptable applicability of the model, an optimal ANN with the lowest MSE value and R values were created and re-trained. 10 different types of network architectures were used to obtain the best model. Six models consist of one hidden layer and four models consist of two hidden layers. The number of neurons in each network was randomly selected. To obtain the optimal architecture, a different number of hidden layers and neurons were examined for each layer.

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Figure 4 shows iterations to determine the optimal architecture. The optimal architecture is represented by 33- 10-1, which means that the optimal number of hidden layers is 1 and the optimal number of hidden neurons representing the complexity of the network is 10, 33 in the first layer as the input layer and 1 in the third layer as the output layer with MSE and R about 0.39474 and 0.99552 respectively.

Table 2 shows the result obtained after applying different activation functions to model 33-10-1. It can be seen that the results vary between the activation functions because the values of the weights between input and hidden layers, the weights between hidden and output layers, and the bias values in the hidden layer are chosen randomly. At epochs 3000, tansig-tansig gave the optimal value of correlation coefficient, R of 0.99687 and MSE 0.31822. While at epochs 2000, logsig-logsig gave optimal values of correlation coefficient R of 0.99856 and MSE of 0.14558. However, the best activation function was logsig-purelin with epochs 1000 and the optimal value of correlation coefficient, R of 0.99888 and MSE of 0.00085. This function was chosen because the optimal value of R is almost one and MSE is close to zero.

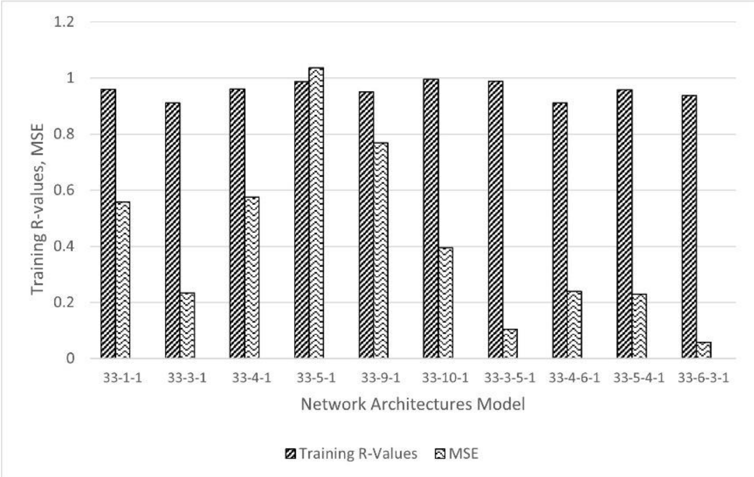

Figure 4: Comparison between network Architecture Model.

Table 2: Results obtained for ANN Models Performance

Activation Function	Evaluation Criteria			
	Epochs	Rtrain1	MSE	RMSE
tansig-tansig	3000	0.99687	0.31822	0.56411
logsig-tansig	2000	0.99856	0.14558	0.38155
logsig-purelin	1000	0.99888	0.00085	0.02915

Figure 5 shows the correlation between the predicted and actual shear strength data obtained with the 33-10-1 model. The model, when trained with the Logsig-Purelin activation function, achieved higher accuracy and precision concerning the targeted value of the result. This is an indication that there are no discrepancies between the present ideal line of agreement. All prediction methods have values that are close to each other at low shear strengths. The logsig-purelin activation function proved to be the most suitable for the application of this study. The results show that the best correlation coefficient is 0.99888 for training, 0.99239 for testing, and 0.99997 for validation.

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Table 3 shows the summarized form of the results obtained to determine the predictive ability of the shear strength of the model ANN based on the experimental data sets. The model ANN with all 33 input variables and the architecture network model 33-10-1 is very close to the ideal model. This is because the total error from the test data sets is lower compared to the training values.

Several features and parameters of the ANN model were changed and modified to obtain a prediction model with high accuracy and low error. Thus, it is possible to increase the number of neurons in the hidden layer and the number of neurons in each network model. When the number of neurons in the hidden layer and the number of epochs in each network model are changed, acceptable predictions of concrete shear strength are obtained.

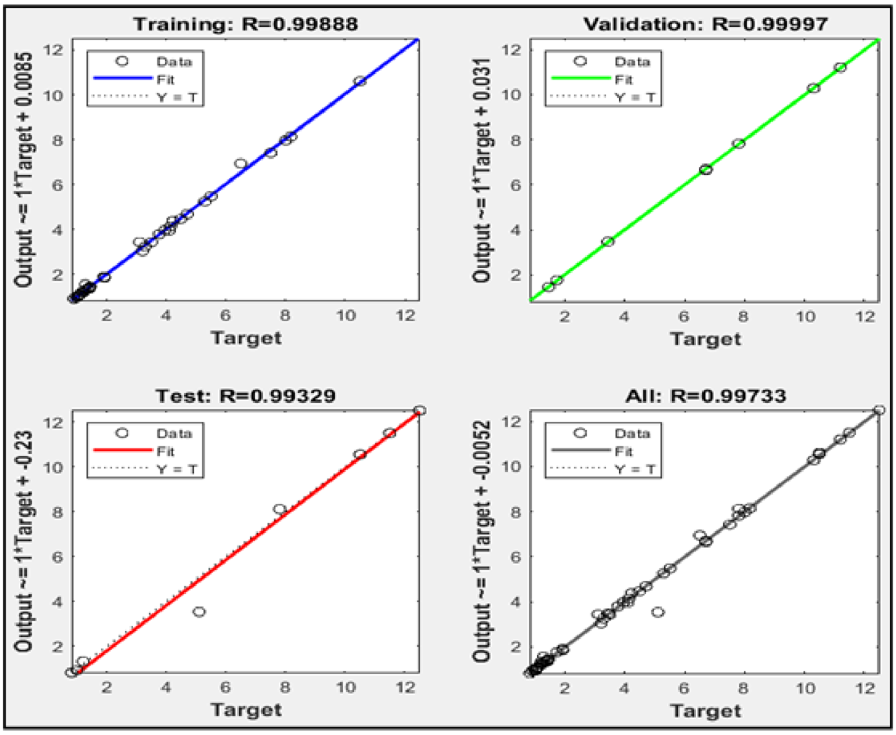

Figure 5: Scatter diagrams for Training, Testing and Validation Predicted Results

Table 3: Statistical Analysis of the Model Performance

ANN Architecture Model	33-10-1

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Type of Architecture	Multilayer Feed-Forward Backpropagation
Transfer Function	Logsig-Purelin (Hidden +Output)
Input Layer	1 (33 Neuron Numbers)
Hidden Layer	1 (10 Neuron Numbers)
Output Layer	1 (1 Neuron Numbers)
Epochs	1000 Epochs
Training R-values	0.99888
Testing R-values	0.99329
Validation R-values	0.99997
MSE	0.00085
RMSE	0.02915

3.2 Comparison between the Experimental and the Predicted Shear Strength

Figure 6 shows the comparison between the result of ANN and the previously collected experimental data sets. The total of 51 data sets used to train ANN show a very systematic increase and decrease in a line shape, following the shape of the line of experimental shear strength values very closely. This indicates that the network systems adapted very well to all parameters of shear strength of concrete mixtures throughout the training process. On the other hand, the overall performance of the ANN system during the tests in Figure 6 was also satisfactory as it showed a strong connection between the experimental and predicted results. The highest shear strength of concrete from the experiment is 12.50 MPa and 12.499 MPa for predicted shear strength in data set 18 (out of 51 data sets).

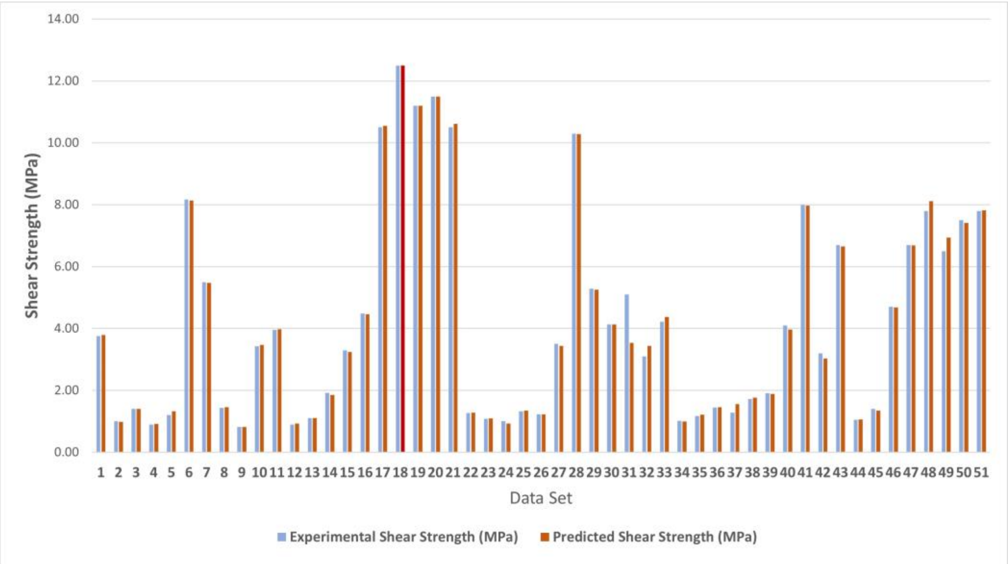

Figure 6: Comparison between the Outputs of the Datasets and The Optimum ANN Model for Shear Strength

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4. CONCLUSIONS

The main goal of this study is to find the optimal network for predicting shear strength by changing the size of the test set and the number of neurons in the hidden layer. The following conclusions are presented in this study where the optimum values of MSE of the optimal ANN model were 0.00085. The optimal ANN architecture model is 33-10-1, i.e., 33 input parameters, 1 hidden layer with 10 neurons, and 1 output layer. The performance of the 33-10-1 architecture was better than the other architectural models with the optimal value of correlation coefficient, R of 0.99888 and MSE of 0.00085.

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REFERENCES

[1] A. M. al-Swaidani, and W.T. Khwies, “Applicability of artificial neural networks to predict mechanical and permeability properties of volcanic scoria-based concrete”, *Advances in Civil Engineering*, vol. 2018, no. 4, Oct., pp. 1-16, 2018.

[2] J. Amani, and R. Moeini, “Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network”, *Scientia Iranica*, vol. 19, no. 2, Apr., pp. 242–248, 2012.

[3] O. Munashico C, and D. Dinebari D, “Prediction of concrete strength using artificial neural network”. *International Journal of Advanced Research and Publications*, vol. 1, no. 6, Dec., pp. 74-77, 2017.

[4] B. K. A. Mohamad Ali Ridho, C. Ngamkhanong, and Y. Wu, “Recycled aggregates concrete compressive strength prediction using artificial neural networks (ANNs)”. *Infrastructures*, vol. 6, no. 2, Jan., pp. 1-20, 2021.

[5] H. Naderpour, M. Sharei, P. Fakharian and MA. Heravi, “Shear strength prediction of reinforced concrete shear wall using ANN, GMDH-NN and GEP”, *Journal of Soft Computing in Civil Engineering*, vol. 6, no. 1, Jan., pp. 66-87, 2022.

[6] J.-S. Chou and N. Ngoc-Tri, “Predicting shear strength of reinforced concrete deep beams using artificial intelligence”, 2014.

[7] M. Ogbodo and D. Dinebari, “Prediction Of Concrete Strength Using Artificial Neural Network”, *International Journal of Advanced Research and Publications*, vol. 1, no. 6, pp. 1-5, 2017.

[8] Q.H. Nguyen,H.-B. Ly,T.-A. Nguyen, V.H. Phan, L. K. Nguyen and V.Q. Tran, “Investigation of ANN architecture for predicting shear strength of fiber reinforcement bars concrete beams”, *PLoS ONE*, vol. 16, no. 4, pp. 1-22, 2021.

[9] O., Iruansi, M. Guadagnini, K. Pilakoutas and K. Neocleous, “Predicting the Shear Strength of RC Beams without Stirrups Using Bayesian Neural Network”, 4th International Workshop on Reliable Engineering Computing, Robust Design--Coping with Hazards, Risk and Uncertainty, pp. 597-613. 2010.

[10] M. Nikoo, B. Aminnejad and A. Lork, “Predicting shear strength in FRP-reinforced concrete beams using Bat Algorithm-Based Artificial Neural Network”, *Advances in Materials Science and Engineering*, vol. 2021, pp. 1-13, 2021.

[11] M. Arafa, M. Alqedra, and H. An-Najjar, “Neural network models for predicting the shear strength of reinforced normal and high-strength concrete deep beam”. *Journal of Applied Sciences*, vol. 11, no. 2, Feb., pp. 266-274, 2011.

p-ISSN 1675-7939; e-ISSN 2289-934

[12] A. Ababneh, M. Alhassan, and M. Abu-Haifa, “Predicting the contribution of recycled aggregate concrete to the shear capacity of beams without transverse reinforcement using artificial neural networks”, *Case Study in Construction Materials*, vol. 13, Dec., pp. 1-13, 2020.
[13] J.A. Abdalla, A. Elsanosi, and A. Abdelwahab, “Modeling and simulation of shear resistance of R / C beams using artificial neural network”, *Journal of the Franklin Institute*, vol. 344, no. 5, Aug., pp. 741-756, 2007.
[14] X. Li, C. Yuan, and B. Shan, “System identification of neural signal transmission based on backpropagation neural network”, *Mathematical Problems in Engineering*, vol. 2020, no. 1, Aug., pp. 1-8, 2020.
[15] Chandrashekharamurthy H. K , Prathap Kumar M. T and Prema Kumar W. P, “Shear strength, compressive strength and workability characteristics of concretes reinforced with steel fibres,” *International Journal of Engineering Research & Technology* (IJERT).Vol. 8, Issue 6, Jun., pp. 10-13, 2019.
[16] F. Xie, “Combined compression-shear performance and failure criteria of internally cured concrete with super absorbent polymer.” *Construction and Building Materials*. Vol. 266, Jan, 2021.
[17] H. Katkhuda and N. Shatarat, “Shear behavior of reinforced concrete beams using treated recycled concrete aggregate,” *Construction and Building Materials*, vol. 125, Aug., pp. 63-71, 2016.
[18] J. Liu, Z. Chen, D. Guan, Z. Lin and Z. Guo, “Experimental study on interfacial shear behaviour between ultra-high performance concrete and normal strength concrete in precast composite members,” *Construction and Building Materials*, vol. 261, Nov. 2020.
[19] K. Nakarai, M. Shigemitsu, E.Masaki, and M. Shota, “Shear strength of reinforced concrete beams: concrete volumetric change effects,” *Journal of Advanced Concrete Technology*, vol. 4, May., pp.229-244, 2016.
[20] M. Arezoumandi, and J. Volz, An experimental study on shear strength of chemically-based self-consolidating concrete. “*International Journal of Concrete Structures and Materials*,” vol. 7, no. 4, Dec., pp.273-285, 2013.
[21] M. Arezoumandi, J. Volz, C. Ortega and J. Myers, “Effect of total cementitious content on shear strength of high-volume fly ash concrete beams.” *Materials and Design*. vol. 46, Apr., pp. 301-309, 2013.
[22] M. Leone, G. Centonze, D. Colonna, F. Micelli and M.A. Aiello, “Fiber-reinforced concrete with low content of recycled steel fiber: Shear behaviour,” *Construction and Building Materials*,vol 161, Nov., pp. 141-155, 2017.
[23] N. S. Alimrani and G. L. Balazs, “Synthetic fibres or fibre cocktail in terms of shear capacity of concrete after elevated temperatures,” *Mechanics of Materials*, vol. 148, Sep. 2020.
[24] Noor S. Yacob, Mohamed A. ElGawady, Lesley H. Sneed and Aly Said, “Shear strength of fly ash-based geopolymer reinforced concrete beams,” *Engineering Structures*, vol. 196, Oct. 2019.
[25] R.Manjunath, M. C. Narasimhan, M.Shashanka, S.D.Vijayanand and J.Vinayaka, “Experimental studies on shear strength characteristics of alkali activated slag concrete mixes,” *Materials Today: Proceedings*, vol. 27, part 1, Dec., pp. 275-279, 2019.
[26] S.-B. Kang, K. H. Tan, X.-H. Zhou, and B. Yang, “Experimental investigation on shear strength of engineered cementitious composites,” *Engineering Structures*, vol. 143, Apr., pp. 141-151, 2017.
[27] T. Tahenni, M. Chemrouk and T. Lecompte, “Effect of steel fibers on the shear behavior of high strength concrete beams,” *Construction and Building Materials*, vol. 105, Feb., pp. 14-28, 2016.
[28] X. Xue, X. Hua and J. Zhou, “Test and prediction of shear strength for the steel fiber–reinforced concrete beams,” *Advances in Mechanical Engineering*, Vol. 11, no. 4., Apr., pp. 1–14. 2019.
[29] Y. Zhang, P. Zhu, X. Wang and J. Wu, “Shear properties of the interface between ultra-high performance concrete and normal strength concrete,” *Construction and Building Materials*, vol. 248, Jul. 2020.

p-ISSN 1675-7939; e-ISSN 2289-934

[30] Z. Liu, J. Jia, W. Feng, F. Ma and C. Zheng “Shear strength of cemented sand gravel and rock materials,” *Sains Malaysiana*, vol. 46, no. 11, pp. 2101-2108, 2017.

[31] A. Shahbazian, H. Rabiefar and B. Aminnejad, “Shear strength determination in rc beams using ann trained with tabu search training algorithm,” *Advances in Civil Engineering,* vol. 202, 14 pages, https://doi.org/10.1155/2021/1639214.

[32] J. Rajeev, S. Pramod and B. Sanjay, “Unconsolidated undrained shear strength of remoulded clays by anns technique,” *International Journal of Engineering Research & Technology (IJERT),* vol. 02, Issue 06, Jun. 2013.

[33] T.-A. Nguyen, H.-B. Ly, H.-V. Thi Mai and V. Q. Tran, “On the training algorithms for artificial neural network in predicting the shear strength of deep beams,” *Complexity,* vol. 2021, 18 pages, https://doi.org/10.1155/2021/5548988.

[34] Q. H. Nguyen, H.-B. Ly, L. S. Ho et al. “Influence of data splitting on performance of machine learning models in prediction of shear strength of soil,” *Mathematical Problems in Engineering*, 2021.

[35] Y. Xu and R. Goodacre, “On splitting training and validation set: a comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning,” *Journal of Analysis and Testing*. vol. 2 no. 3, Oct., 2018.

[36] A. Ranganathan, “The levenberg-marquardt algorithm,” June 2004

[37] D. Baptista and F. Morgado-Dias, “Comparing different levenberg-marquardt algorithm implementations,” Conference: Controlo’2012 At: Funchal, Portugal, 2012.

[38] “Activation function in neural networks,” Sep. 2020.

[39] M. Saheed, “A gentle introduction to sigmoid function,” 25 Aug. 2021,

[40] S. Ngah and R. Abu Bakar, “Sigmoid function implementation using the unequal segmentation of differential lookup table and second order nonlinear function,” *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 9. No.2-8, Sep., pp. 103-108, 2017.

[41] A. M. N. El-Khoja, A. F. Ashour, J. Abdalhmid, X. Dai, and A. Khan, “Prediction of rubberised concrete strength by using artificial neural networks”, *International of Journal Structural and Construction Engineering,* vol. 12, no. 11,Nov., pp. 1068–1073, 2018.

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