

Received:

8 August 2018

Revised:

9 December 2018

Accepted:

28 December 2018

Cite as: T. F. Awolusi, O. L. Oke, O. O. Akinkulore, A. O. Sojobi, O. G. Aluko. Performance comparison of neural network training algorithms in the modeling properties of steel fiber reinforced concrete. *Heliyon* 5 (2019) e01115. doi: [10.1016/j.heliyon.2018.e01115](https://doi.org/10.1016/j.heliyon.2018.e01115)



Performance comparison of neural network training algorithms in the modeling properties of steel fiber reinforced concrete

T. F. Awolusi^{a,*}, O. L. Oke^a, O. O. Akinkulore^a, A. O. Sojobi^b, O. G. Aluko^a

^a Department of Civil Engineering, Ekiti State University, Ado — Ekiti, Ekiti State, Nigeria

^b Department of Architecture and Civil Engineering, City University of Hong Kong, Kowloon, Hong Kong, China

* Corresponding author.

E-mail addresses: temitopeawolusi06@gmail.com, temitope.awolusi@eksu.edu.ng (T.F. Awolusi).

Abstract

Our study is aimed at modeling the effect of three contributory factors, namely aspect ratio, water cement ratio and cement content on the water intake/absorption, compressive strength, flexural strength, split tensile strength and slump properties of steel fiber reinforced concrete. Artificial neural network (ANN) as a multilayer perceptron normal feed forward network was integrated to develop a predictive model for the aforementioned properties. Five training algorithms belonging to three classes: gradient descent, Levenberg Marquardt (quasi Newton) and genetic algorithm (GA). The ANN configuration consists of the input layer with three nodes, a single hidden layer of ten nodes of the output layer with five nodes. The study also compared the performance of all algorithms with regards to their predicting abilities. The ANN training was done by splitting the experimental data into the training and testing set. The divergence of the RMSE between the output and target values of the test set was monitored and used as a criterion to stop training. Although the convergence speed of GA was far higher than all other training algorithm, it performed better in predicting the water intake/absorption, split tensile strength and slump properties. However,

incremental back propagation (IBP) and batch back propagation (BBP) outperformed GA in predicting the compressive strength and flexural strength respectively. The overall performance of the training algorithm was assessed using the coefficient of determination and the absolute fraction of variance obtained for the test data set and GA was found to have the highest value of 0.94 and 0.92 respectively. In determining the properties fiber reinforced concrete according to GA–ANN implementation, the water/cement ratio played slightly more dominant role than the aspect ratio and this was followed by cement content.

Keywords: Civil engineering, Computer science

1. Introduction

The application of artificial neural networks (ANNs) for prediction and optimization of concrete properties is relatively a new research area and recent studies have demonstrated that ANN is one of the best machine learning tools for this purpose (Chopra et al., 2015; Muthupriya et al., 2011; Torre et al., 2015). The comparison between ANN and some classical modeling techniques such as response surface methodology (RSM), Plackett-Burman designs, full factorial designs and randomized block designs showed the supremacy of ANN as a modeling technique in analyzing non-linear relationships of data sets, which consequently provides good fitting for data and as well as better predictive ability (Hacene et al., 2013).

Artificial neural network can be described as a simplified model with a structure similar to a biological network. It imitates the ability of the human brain in performing neurological processes (Ghoushchi, 2015). Through iteration process, the network learns from examples and continues the iteration process until the output is in conformity with the provided response based on the specified level of accuracy. Every example consists of series of inputs and corresponding outputs also known as responses and the network makes changes through the internal connections known as weights (Shihani et al., 2006; Muthupriya et al., 2011; Altarazi et al., 2018; Muthupriya et al., 2011).

In recent times, the application of ANN as a prediction tool by a wide range of discipline including engineering has been on the increase, due to their capability to utilize learning algorithm and recognize input and output relationship for non-linear, complex systems (Alavala, 2008; Zobel and Cook, 2011; Pilkington et al., 2014). ANN technique possesses great potentials for experimental modeling and optimization due to their ability to understand the interaction behind complex processes (Ebrahimipour et al. (2008). ANN is suitable in engineering research since most problems in engineering are non-linear in nature.

Several training algorithms have been explored in ANN such as Powell- Beale conjugate algorithm, Palk-Ribiere conjugate gradient algorithm, Levenberg Marquardt, Scaled conjugate gradient back propagation, resilient back propagation, one step secant back propagation, Fletcher-reeves conjugate gradient algorithm and Quasi-Newton algorithm with Broyden, Fletcher, Goldfrab and Shanno (BFGS) alongside different network architectural parameters. Compared to other training algorithms, LM with tan-sigmoid transfer function was reported to give the best prediction efficiency for concrete compressive strength (Chopra et al., 2015).

Also, multilayer perceptron back propagation algorithm of ANN and multi-layered feed forward with back propagation algorithm of ANN were found suitable for predicting the compressive strength and durability of concrete with good level of accuracy (Hacene et al., 2013; Muthupriya et al., 2011). Also, several number of non-linear functions are available in ANN such as sigmoid, Tanh, Gaussian, Linear, Threshold Linear, Bipolar Linear (CPC-X software 2003). The sigmoid function was observed to be the most commonly used function (Muthupriya et al., 2011).

In the multilayer normal feed forward connection, information flows only in one direction, that is from the input layer through the hidden layer to the output layer, while the multilayer full feed forward accommodates direct connection between the input layer and the output layer as shown in Fig. 1 (a) and (b).

Furthermore, although there are a number of learning algorithms, the back propagation (BP) also known as Delta-rule algorithms is most often used. Training of the neural network is carried out to match the set of input data fed into the network through iterative adjustment of weights. In this process the weights between neurons is optimized during the learning or training process by the backward propagation of the error. The performance of the ANN was statistically measured by the root mean square error (RMSE), mean prediction error (MPE), using Eqs. (1) and (2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_{pre,i} - O_{exp,i})^2}{n}} \quad (1)$$

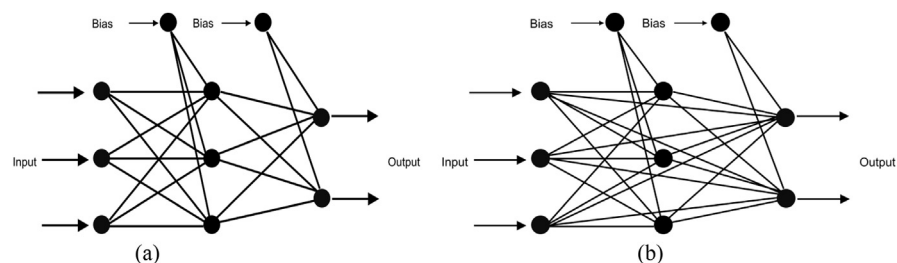


Fig. 1. (a) Multi-layer normal feed forward (b) Multi-layer full feed forward (CPC-X Software 2003).

$$MPE = \frac{\sum (O_{pre,i} - O_{exp,i})}{n} \quad (2)$$

where the predicted output for observation i is $O_{pre,i}$, the experimental output is $O_{exp,i}$ obtained for the observation i and n is the total number of data obs.

Other training algorithms available in ANN include gradient descent back propagation algorithms and genetic algorithm (GA). The gradient descent back propagation measures the output error and calculates the error gradient making necessary adjustment to the ANN weights in a descending gradient direction. There are three kinds of gradient descent back propagation algorithms namely incremental back propagation (IBP), batch back propagation (BBP) and quick propagation (QP). While BBP algorithm performs updating of the network weights once per iteration, as well as processing all the learning data pattern through the network, IBP performs updating of the network weights when every pattern in the learning data set has been presented, instead of updating the weights once per iteration (Ghaffari et al., 2006; CPC-X Software, 2003). QP is a modified back propagation equipped with fast processing time.

On the other hand, GA has the advantage of acquiring an optimal solution from a generational search instead of the one point (local) search employed by the gradient descent and Levenberg Marquardt algorithm. The search is done according to predefined objective functions such as reproduction, crossover, and mutation (Fang et al., 2005; Ghaffari et al., 2006). Also, compared to gradient descent algorithm, LM has the advantage of stability and fast convergence and has been useful in several modeling techniques (Sakamoto et al., 2005).

Recently, the need for sustainability in the construction industry, has brought about the incorporation of numerous wastes in concrete (Thomas et al., 2014; Prusty and Sanjaya, 2015; Maddalena et al., 2014). One of such wastes is steel fiber obtained from discarded tyres. Various researches in this area has found the material suitable for use as reinforcement in concrete and a suitable replacement for industrial steel fibres (Pilakoutas et al., 2004; Gregory, 2005; Papakonstantino and Tobolski, 2006; Aiello et al., 2009; Mohamad, 2011; Syaidathul and Izni, 2012; Onuaguluchi and Banthia, 2018). Furthermore, steel fibers have been identified as having the advantage of reducing the brittle nature of concrete as well as improving the mechanical properties of concrete (Chanh, 2004; Sawant et al., 2015; Hameed et al., 2009; Lee et al., 2015; Yang et al., 2011).

In addition, different studies reported that addition of moderate quantities of steel fibres improved the compressive strength (CS), flexural strengths (FS) and tensile strengths of conventional concrete with improved crack control as a result of improved bonding (Pilakoutas et al., 2004; Syaidathul and Izni, 2012). The studies also reiterated the need for development of rapid and reliable prediction model to

give an insight into the fresh and hardened mechanical properties of this concrete to encourage its application in the construction industry.

Therefore, the aim of our study is to identify the best ANN training algorithm for modeling the fresh and hardened properties of steel fibre reinforced concrete (SFRC). The five learning algorithm of ANN explored in this study were incremental back propagation, batch back propagation and quick propagation, Levenberg Marquardt and genetic algorithm. The objectives of our study are:

1. Identify the best ANN training algorithm to model the fresh and hardened properties of steel fibre reinforced concrete
2. Evaluate the interactions of the investigated variables such as water-cement ratio, steel fibre aspect ratio and cement content on the fresh and hardened properties of SFRC utilizing the identified best ANN training algorithm.

2. Materials and methods

The Dangote brand of Ordinary Portland cement (Grade 42.5) purchased in Ado Ekiti local market was used, limestone obtained from a natural deposit available at Obajana, was ground to powder and used as filler. The particle size distribution is presented in Fig. 2. From Fig. 2, it could be observed that the limestone powder obtained had particle sizes very close to that of the cement used. The coarse aggregate was granite of maximum size 20 mm obtained from a construction site in the premises of Ekiti State University (EKSU), Ado Ekiti. The sand used as fine aggregate was obtained from a river bank close to EKSU campus. Fig. 2 also presents the particle size distribution of the both coarse and fine aggregates. A proprietary

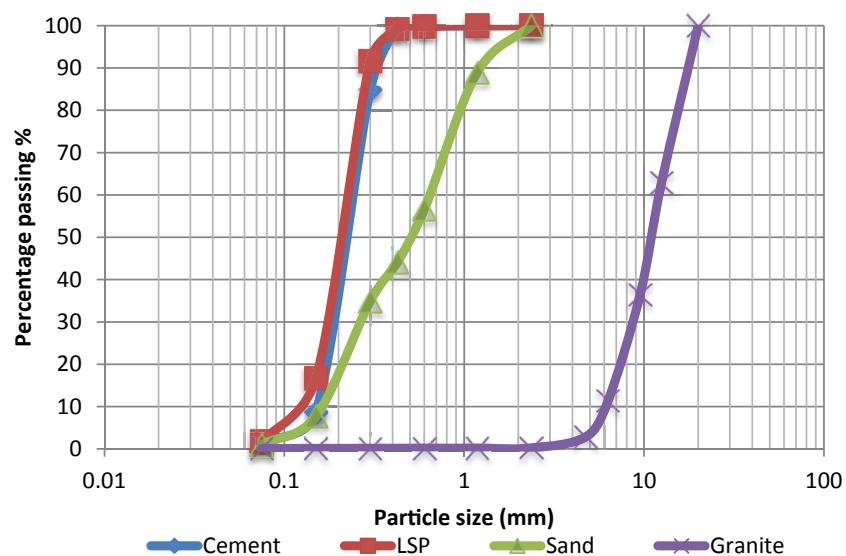


Fig. 2. Grading curve for materials.

superplasticizer Betocrete-F4 kindly provided by Advanced Chemical Technology, Ikeja was used to enhance workability of the concrete. The steel fibers used were 0.25 mm shredded into different lengths (see Fig. 3). The volumetric fraction of steel fiber was kept constant at 1%. Potable water suitable for domestic purpose was used in concrete mixing.

All materials were mix in a laboratory mixer with a uniform speed of sixty (60) revolution per minute (rpm). The mixing procedure is shown in Fig. 4. The workability of all mixtures was determined by means of slump test. Mixtures were cast into the $100 \times 100 \times 100 \text{ mm}^3$ cubes for water absorption, compressive and split tensile strengths test. For the flexural strength test mixture were cast into $400 \times 100 \times 100 \text{ mm}^3$ beams. All mixtures were manually compacted in three layers using a tampering rod. After casting, samples were kept in a laboratory ($29 \pm 2^\circ\text{C}$) for twenty four hours (24) before demoulding. After demoulding, the samples were kept in water until the day of testing. The water absorption test was carried out after 24 hours of immersing samples in water while the compressive, split tensile and flexural strengths test was carried out at 28 days.

Slump test was carried out according to BS EN 12350-2 (2009) while water absorption was carried out according to BS EN 12390-3 (2009). Also, flexural strength was carried out in accordance with BS EN 12390-5 (2009) using four-point loading test while splitting tensile strength test was done in compliance with BS EN 12390-6 (2009).

The slump measured in centimeter (cm) was the difference between the highest surface point of the concrete specimen to the underside of the tamping rod placed on top of the inverted slump cone mould after removal of excess concrete.

Water absorption was calculated according to Eq. (3).

$$\text{Water absorption} = \frac{W_2 - W_1}{W_1} \times 100 \quad (3)$$

where W_2 = Weight of sample before immersion in water

W_1 = Weight of sample after immersion in water

The compressive strength of each specimen was evaluated from the maximum crushing load in Newton (N) obtained from the compressive testing machine divided by the effective area in millimeter (mm) as shown in Eq. (4).

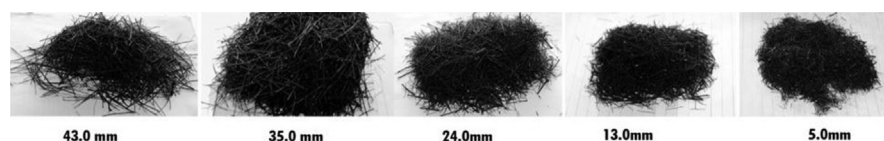


Fig. 3. Different lengths of shredded waste tyre steel fibers with different aspect ratios.

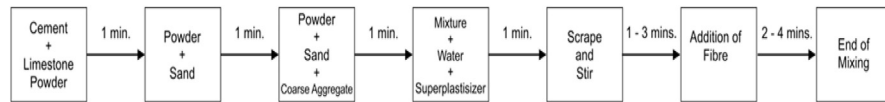


Fig. 4. Simplified flow chart for production of steel fiber reinforced concrete.

$$\text{Compressive strength} = \frac{\text{Maximum crushing load}}{\text{Surface area of specimen}} \quad (4)$$

The flexural strength of each specimen was determined using Eq. (5).

$$R = \frac{3Fl}{4bd^2} \quad (5)$$

where R = Flexural strength (N/mm²)

L = Span of the beam (mm)

b = breadth of beam (mm)

d = depth of beam (mm)

The split tensile strength of each specimen was evaluated according to Eq. (6).

$$F_t = \frac{2P}{(\pi DL)} \quad (6)$$

where F_t = Tensile strength (N/mm²)

P = Load at failure (N)

D = Diameter of cylinder or side of the cube (mm)

L = Length of the cylinder/cube (mm)

The factors considered in the design were aspect ratio (A) water/cement ratio (B) and % cement content. These factors were investigated for their impact on the performance of concrete reinforced with steel fibers. The properties evaluated are water intake/absorption, Compressive strength, split tensile strength and flexural strength and slump. The variation in aspect ratio was a function of the length to diameter ranged from 50 to 140. This variation in aspect ratio was determined by changes in length of steel fiber since the diameter of extracted steel fiber was 0.25 mm. Pilakoutas et al. (2004) observed that the diameter of steel fiber extracted through shredding was about 0.23 mm which is close to what was observed in the study. The water/cement ratio was varied between 0.25 and 0.4 due to the presence of superplasticizer. The superplasticizer was added at 3% by weight of cement. The percentage cement content was varied between 25 and 40. A central composite design (CCD) which allows the inclusion of axial experimental point was used in determining the experimental condition. The CCD is usually required in examining larger spread conditions where accurate prediction is required for a model with an unknown complexity (Pilkington et al., 2014). A three factors experimental matrix presented

Table 1. CCD experimental conditions and mechanical properties steel fibre reinforced concrete.

Run No.	Aspect ratio (A)	Water/ratio (B)	Cement (C)	Water intake/absorption (%)	Compressive strength (N/mm ²)	Flexural strength (N/mm ²)	Split tensile strength (N/mm ²)	Slump (cm)
1	140(+1)	0.25(−1)	25(−1)	0.493	30.4	5.4	6.4	0
2	50(−1)	0.25(−1)	25(−1)	0.205	33	7.8	5.1	0
3	140(+1)	0.4(+1)	25(−1)	0.278	22	6.8	5.1	22
4	50(−1)	0.4(+1)	25(−1)	1.08	22	6.4	6.5	23
5	95(0)	0.325(0)	32.5(0)	1.086	32.1	7.65	6.9	11
6	140(1+)	0.25(−1)	40(+1)	0.589	46.5	8.3	5.7	8.9
7	140(+1)	0.4(+1)	40(+1)	1.097	23.8	5.6	8.9	29
8	95(0)	0.325(0)	32.5(0)	0.976	32	7.9	6.8	10
9	95(0)	0.325(0)	19.88(−α)	0.785	28	6.4	6.1	2
10	95(0)	0.325(0)	45.11(+ α)	1.387	24	6.5	5.9	17
11	19.32(− α)	0.325(0)	32.5(0)	1.102	30.5	6.9	4.5	10
12	95(0)	0.325(0)	32.5(0)	1.275	31.8	7.4	6.9	12
13	95(0)	0.325(0)	32.5(0)	1.106	32	7.425	7	11
14	50(−1)	0.25(−1)	40(+1)	1.125	36.4	7.2	4.8	9
15	95(0)	0.325(0)	32.5(0)	0.911	32.2	7.4	6.72	10
16	50(−1)	0.4(+1)	40(+1)	0.894	24	6.21	4.3	27
17	95(0)	0.325(0)	32.5(0)	1.02	31.8	7.53	6.9	11
18	170.68(+ α)	0.325(0)	32.5(0)	1.219	28.5	6.5	4	3
19	95(0)	0.45(+ α)	32.5(0)	1.349	17.8	6.8	4.5	28
20	95(0)	0.2(− α)	32.5(0)	1.741	11.3	3	3.84	0

The test data set are presented in bold characters.

in Table 1 was developed using Design expert V.8, a total of 20 runs which includes eight (8) factorial points, six (6) center points and six (6) axial points. In coded terms the experimental conditions is expressed as $-\alpha$, -1 , 0 , 1 , $+\alpha$. Where $\alpha = 1.633$.

The aforementioned factors were used as the inputs to the network while the properties of steel fiber reinforced concrete investigated were the output of the neurons. The output neurons comprise of a total of five (5) nodes with each node represents the one property as illustration in Fig. 5. In determining the number of hidden layers to be used in the ANN training the study utilized the recommendations of Hush and Horne (1993) by using a single hidden layer since there was no improvement in the performance of the ANN network with increased number of hidden layers. In order to determine the number of nodes in the hidden layer a try and error process was used. The study started this process initially with five (5) neurons in the hidden layer and this number was increased until a minimum RMSE was observed using ten (10) nodes. The final MLP normal feed forward network used for training is designated as a 3:10:5 where three (3) represents the input neurons, ten (10) represents the hidden neuron and five (5) represents the output neurons. A transfer function known as sigmoid was used for the hidden and output layers. The sigmoid transfer function has the ability to computes its output to successive layers using Eq. (7). The increase in the value of α strengthens the non-linearity of the sigmoid function. The value of α for the study was one ($\alpha = 1$) (CPC-X Software, 2003):

$$\xi(\mu_k) = \frac{1}{1 + \exp(-\alpha\mu_k)} \quad (7)$$

where:

$\xi(\mu_k)$ = Transfer function

Alpha (α) = slope of transfer function

The ANN training requires two other parameters which are the learning rate and the momentum coefficient. The function of the learning rate is to adjust the speed of the

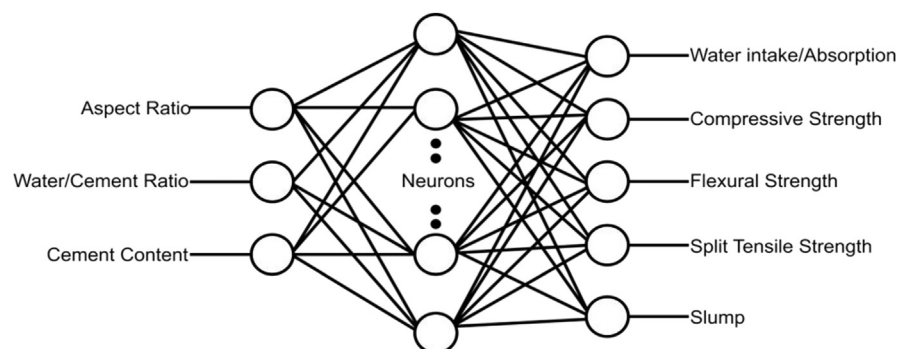


Fig. 5. A multilayer perception normal feed forward network used in training and modeling properties of steel fibre reinforced concrete.

learning process. When it is fast the model learns faster and when it is too high, the convergence of the error surface can be impeded due to the oscillation of weight changes and as well overshoot the near optimal weight factor. The ANN model can also be trapped in error of local minimum rather than the global minimum, when the learning rate is too slow. The latter is used by the back propagation of ANN to update weight in order to avoid local minima and as well reduce oscillation of weight changes. A faster learning with no oscillation can be obtained by relating successive change in weight to previous weight change. The Momentum coefficient determines the current weight change by adding a proportion of the previous weight change. A simplified relationship showing the effect of these parameters on weight adjustment is presented in Eq. (8) (Ghaffari et al., 2006):

$$\begin{aligned} \text{New weight change} = & \text{learning rate} \times \text{error} + \text{momentum coefficient} \\ & \times \text{last weight change} \end{aligned} \quad (8)$$

This study utilized the default settings provided by CPC-X Software for learning rate and momentum coefficient. For IBP and BBP the values for learning rate and momentum coefficient are 0.15, and 0.8; 0.1 and 0.4, respectively. For QP the default learning rate is 0.8 while momentum coefficient is not utilized in QP. In the IBP and BBP learning rate and momentum coefficient remains constant all through the training process. In the case of QP, the learning step size is kept as large as possible to ensure learning stability since the learning rate is an adaptive one. In contrast to IBP and BBP the learning rate for QP starts at 0.8 and could increase as long as the network can learn without large error increase (Ghaffari et al., 2006).

In evaluating the ANN, splitting of data into the training and testing subset was carried out. The flow diagram utilized in identifying the best training algorithm is displayed in Fig. 6. Five algorithms were utilized in the ANNs training. The training set of experimental data was used to train the network while the testing set was used to monitor the performance of the network. Both the training and testing data set had corresponding RMSE. Training automatically stop as soon as a minimum RMSE for test set prediction is achieved (Ghaffari et al., 2006). The performance of the system on the test data is used to measure the success of the learning process. These test data are usually not involved in the training process rather they are used in determining the generalization capability of the trained network which ensures that the trained data are not memorized during the learning process.

3. Results and discussion

3.1. Mechanical properties of steel fibre reinforced concrete

The fresh and hard mechanical properties of the steel fibre reinforced concrete are listed in Table 1. In terms of compressive strength, majority of the steel fibre

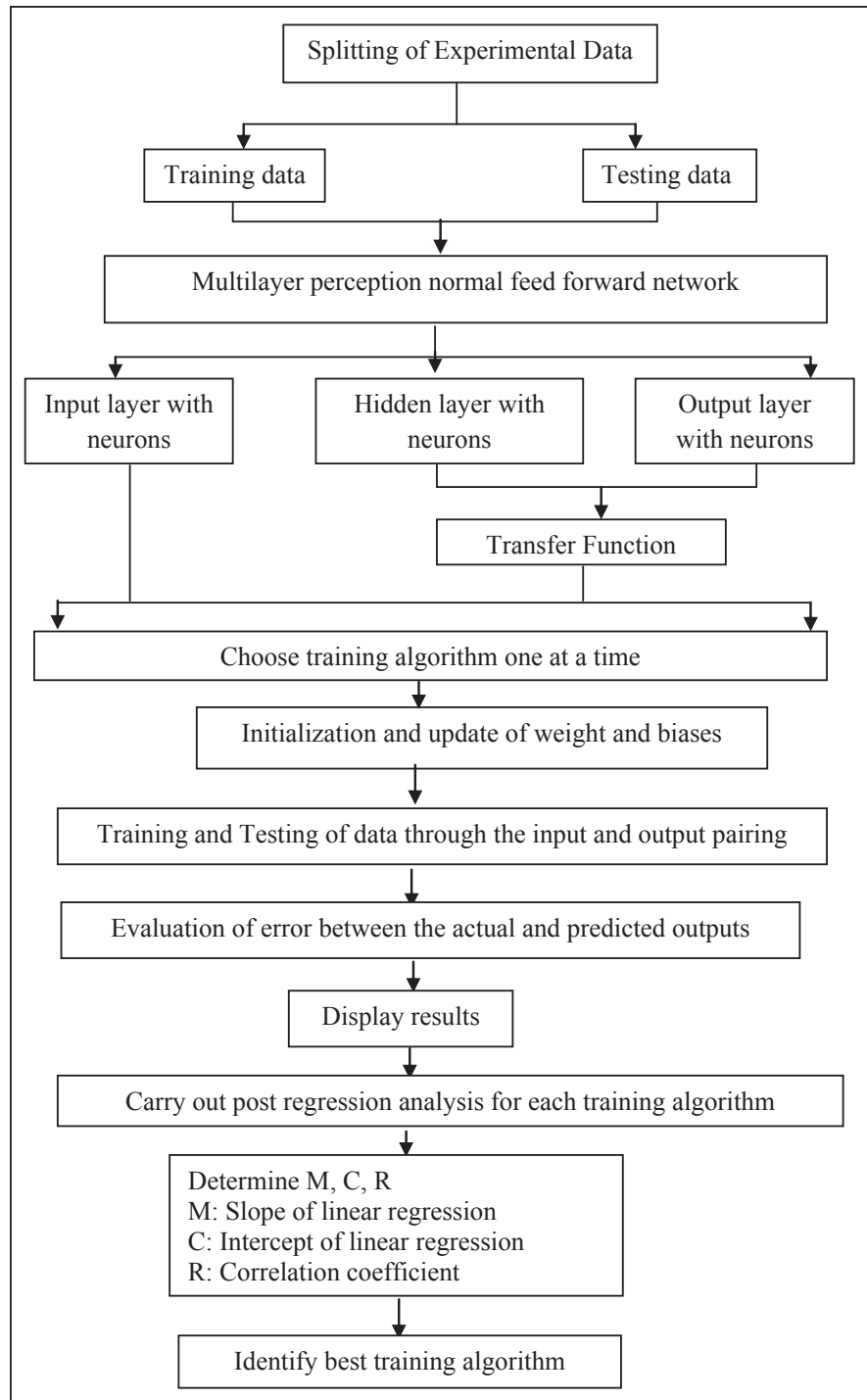


Fig. 6. Flow diagram for identifying the best training algorithm to use in ANN modeling of steel fibre reinforced concrete.

reinforced concrete (SFRC) produced can be classified as normal strength concrete since they fall within 20–39 N/mm² (MPa) with the exception of experiment run 6 SFRC which can be classified as medium-strength concrete since it falls within 40–49 N/mm² (MPa) according to the classification given by [Sojobi et al. \(2018\)](#). Some researchers also obtained similar CS for SFRC ([Aiello et al., 2009](#); [Centonze et al., 2012](#); [Yao et al., 2003](#)). The highest CS of 46.5 N/mm² (MPa) was obtained by steel fibre with aspect ratio of 140, which correspond with steel fibre length of 43 mm. This implies fibre length and aspect ratio influences CS of SFRC. However, CS of experiment run 6 and 7 revealed that CS of SFRC is also influenced by W/C ratio. Though at the same aspect ratio of 140, a higher w/c ratio of 0.4 gave a lower CS of 23.8 N/mm² due to higher slump of the SFRC. Therefore, it can be concluded that high w/c ratio reduces the CS of SFRC owing to the increased fibre dispersion while higher CS of SFRC is obtained at lower w/c ratio, high cement content and higher steel fibre aspect ratio.

It was also observed that a higher slump of SFRC was synonymous to lower CS irrespective of the aspect ratio and cement content. This phenomenon was exhibited by experimental values for runs 3, 4, 7, 14, 16 and 19. In addition, lowest slumps of 0–9 cm were also linked to very low w/c ratio and very low cement content as exhibited by experimental runs 1, 2, 9, 18 and 20. The observed low slumps also caused reduction of the flexural and split tensile strengths of the SFRC. The highest slump of 29 cm was obtained at 0.4 w/c ratio and 40% cement content and can be classified as very high according to the classification given by [Abd Elaty and Ghazy \(2016\)](#). Therefore, it can be concluded that careful selection of w/c ratio and cement content is very important to obtain SFRC with desirable mechanical properties. Similar slump values were obtained in another research ([Aiello et al., 2009](#)). Slump values above 50 mm (5 cm) are desirable for construction applications ([CEALC, 2011](#)). However, the allowable minimum and maximum slump depends on the desired concrete grade which varies from one project to another ([Stanley, 2011](#); [CEALC, 2011](#)).

The flexural strength (FS) of the SFRC ranged from 3 to 8.3 N/mm² (MPa). The highest flexural strength of 8.3 N/mm² was obtained at low w/c ratio of 0.25 w/c and cement content of 40%. A close look at FS values for experiment runs 6, 14 and 2 revealed that high FS were obtained at low w/c ratios, high cement content and high aspect ratio. Therefore, it can be concluded that reinforcing effects of the steel fibres are activated at low w/c ratio, high cement content and high aspect ratio. However, care must be taken to avoid using a low w/c ratio which will result in SFRC of poor workability.

Split tensile strength (STS) values of the SFRC ranged from 3.84 to 8.9 N/mm² (MPa) and were higher than STS values of 2–3.2 MPa reported in another study ([Li et al., 2004](#)). Highest STS of 8.9 MPa was obtained at w/c ratio of 0.4, high

cement content of 40% and high aspect ratio of 140. Conversely, low STS of 3.84 N/mm² was obtained at low w/c ratio of 0.2. A close look at the STS experimental values of runs 1 and 2 at the same w/c ratio and cement content but different aspect ratio and experiment runs 6 and 7 at the same aspect ratio and cement content but different water contents revealed that the effects of w/c on split tensile strength was greater than the effects of aspect ratio.

In addition, the effects of cement content on STS was very minimal when experimental runs 9 and 10 were considered at the same aspect ratio and cement content but different cement contents. Therefore, it can be concluded that careful selection of w/c ratio is paramount to obtain high STS in SFRC.

The water absorption values range from 0.205 to 1.741%. The highest water absorption of 1.741% was recorded by experiment run 20 at low w/c ratio of 0.2. Comparison of experimental result for runs 19 and 20 at the same aspect ratio and cement content but different w/c ratio, revealed that water absorption is higher at low w/c ratio. Comparison of water absorption values of experiment runs 1 and 2 as well as 3 and 4 revealed that short-fibre SFRC with low aspect ratio tend to absorb more water compared to longer-fibre SFRC with high aspect ratio at medium w/c ratio of 0.4. Therefore, it can be concluded that water absorption of SFRC is influenced by the fibre aspect ratio and w/c ratio utilized in the concrete mix.

3.2. Comparison of ANN training results using different algorithms

The study utilized numerical indicators and graphical representation in evaluating the performance of the model as presented in Table 2 and Figs. 7, 8, and 9 respectively. Numerical measures include determination of the optimum epoch at stopping point which gave the least RMSE for the test data set. The CPU time elapsed at the end of training for all algorithms were also compared and details of the CPU time are presented in Table 2. The statistical measures and performance indices for the five learning algorithms is also presented in Table 2. The RMSE and MPE of the test set were used in evaluating the precision and bias respectively. The predicting abilities of the ANN models obtained were verified using five test data set for each property investigated.

From Table 2, a better average accuracy in prediction was observed with GA for the water absorption and split tensile strength, as compared with LM (0.531741 versus 0.549935) and (1.872817 versus 2.200841) respectively. However, the MPE of GA was more than that of LM (0.238413 versus 0.203847) and (2.012567 versus 1.806573). Similarly, GA was also observed to have performed better in predicting slump as compared to LM (5.54189 versus 9.169875). Moreover, GA showed a smaller MPE than that of LM (3.07862 versus 4.802439).

Table 2. Comparison between performance indexes of five training algorithms.

Performance index	Training algorithm				
	IBP	BBP	QP	LM	GA
Water intake/absorption (%)					
Average RMSE test set	0.593029	0.581754	0.626962	0.549935	0.531741
Average RMSE training	0.329321	0.550651	0.550651	0.550651	0.550651
Average MPE	0.246967	0.23984	0.23934	0.203847	0.238413
Compressive strength (N/mm ²)					
Average RMSE test set	5.882287	6.430472	7.309057	8.545643	7.92384
Average RMSE training	7.057267	7.078728	7.019535	7.022993	9.064883
Average MPE	1.916267	1.1804	3.0662	4.542867	5.383267
Flexural strength (N/mm ²)					
Average RMSE test set	1.012813	0.981202	1.000345	1.094486	1.947622
Average RMSE training	1.025659	1.022697	1.016792	1.023099	1.291409
Average MPE	0.214727	0.30676	0.299273	0.43016	0.793073
Split tensile strength (N/mm ²)					
Average RMSE test set	2.759049	2.774263	2.902753	2.200841	1.872817
Average RMSE training	0.553986	0.557682	0.552888	0.553442	1.655808
Average MPE	1.8571	1.83458	1.87544	1.806573	2.012567
Slump (cm)					
Average RMSE test set	9.309544	9.990675	10.82947	9.169875	5.54189
Average RMSE training	5.869869	5.891621	5.859511	5.862201	6.233546
Average MPE	2.697532	2.71032	2.154567	4.802439	3.07862
Average number of epoch at end the end of training	47300	83200	59450	750	20450
Average CPU time elapsed	13	66	7	11	109

For compressive strength, IBP performed better compared to BBP judging by the values of RMSE obtained at the end of testing (5.882287 versus 6.430472). However, the MPE of IBP was more than that of BBP (1.916267 versus 1.1804). From evaluating the RMSE for flexural strength it was observed that BBP perform better when compared to QP (0.981202 versus 1.000345). However, the MPE of IBP was slightly more than that of QP (0.30676 versus 0.299273).

The number of training epochs and time elapsed for total epochs reflecting when the training was terminated, differed drastically among gradient decent modes as well as for Levenberg Marquardt and genetic algorithm (47300 epochs and 13 s for IBP; 83200 epochs and 66 s for BBP; 59450 epochs and 6 s for QP; 750 epochs and 11 s for LM; 20450 epochs and 109 s for GA, respectively). Further analysis on the performance of the ANN-trained models as proposed [Plumb et al. \(2002\)](#) was explored. In this method the ANN predicted values for output of test data set plotted against their corresponding observed values as presented in Figs. 7, 8, and 9. From the linear regression analysis of these agreement plot the gradient (m), intercept (c)

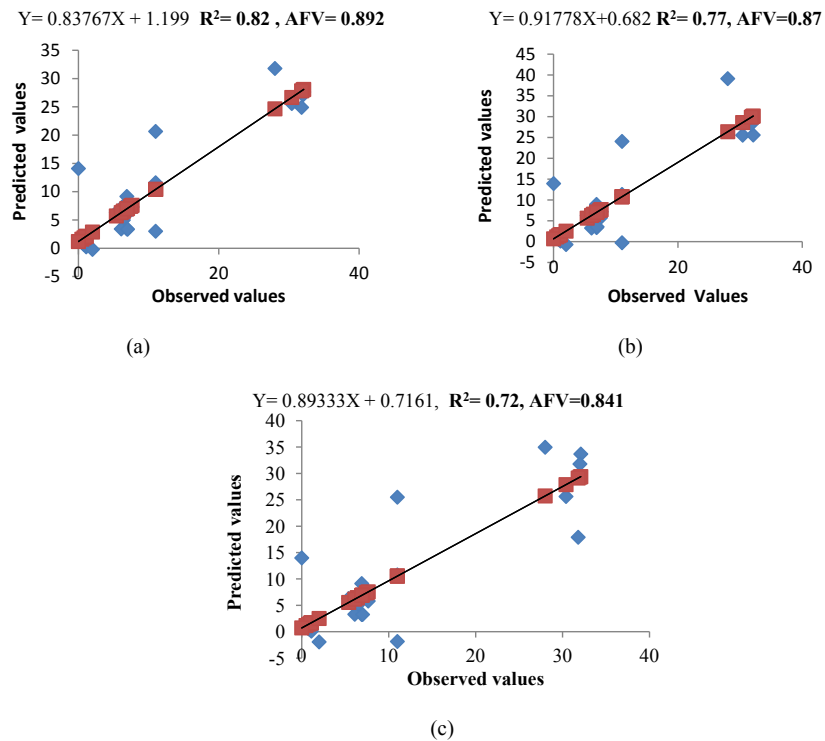


Fig. 7. Scattered plot for observed response (red) versus predicted response (blue) by ANN for the three gradient algorithms: (a) IBP, (b) BBP and (c) QP. The linear regression of the predicted and observed is represented by the straight line.

and good fitness (R^2) was calculated. The aforementioned regression parameters gave a quick and spontaneous appraisal of the model performance. This method of analysis specifies that for a well-trained model the value of m , c and R^2 ($|m$, c , $R|$) obtained for the test data set should be approximately 1, 0 and 1 respectively. For the five learning algorithm the values of $|m$, c , $R^2|$ obtained are $|0.83767$,

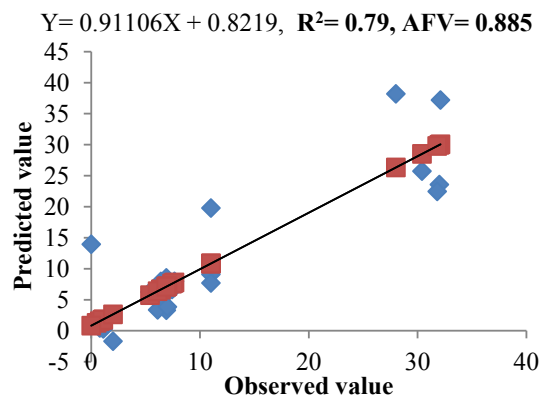


Fig. 8. Scattered plot for observed response (red) versus predicted response (blue) by LM-ANN. The linear regression of the predicted and observed is represented the line.

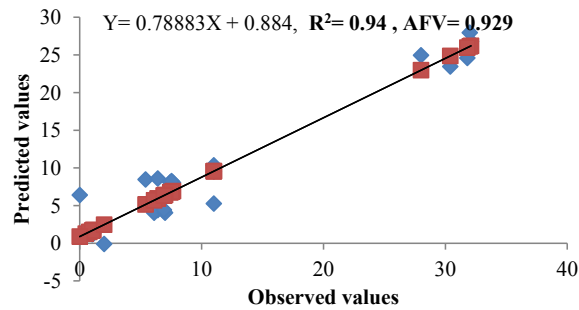


Fig. 9. Scattered plot for observed response (red) versus predicted response (blue) by GA-ANN.

1.199, 0.82], [0.91778, 0.682, 0.77], [0.89333, 0.713, 0.72], [0.91106, 0.822, 0.79] and [0.78883, 0.884, 0.94] for the IBP, BBP, QP, LM and GA respectively. Having obtained divergent views of the performance of the different learning algorithm in predicting the overall properties of concrete reinforced with steel fiber; the robustness of these modeling techniques was evaluated by the coefficient of determination (R^2), the correlation coefficient (R) and the absolute fraction of variance (AFV) of the test data set given by Eqs. (9), (10), and (11) (Moghaddam and Khajeh, 2011; Muthupriya et al., 2011; Uygur et al. 2014).

$$R^2 = 1 - \frac{\sum_{i=1}^n (O_{\text{per},i} - O_{\text{exp},i})^2}{\sum_{i=1}^n (O_{\text{per},i} - O_m)^2} \quad (9)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^n (O_{\text{per},i} - O_{\text{exp},i})^2}{\sum_{i=1}^n (O_{\text{per},i} - O_m)^2}} \quad (10)$$

$$AFV = 1 - \frac{\sum_{i=1}^n (O_{\text{per},i} - O_{\text{exp},i})^2}{\sum_{i=1}^n (O_{\text{exp},i})^2} \quad (11)$$

where the predicted output for observation i is $O_{\text{per},i}$, the experimental output is $O_{\text{exp},i}$ obtained for the observation i O_m is the average of the observed values and n is the total number of data observation.

3.2.1. ANN training using gradient descent algorithm

Comparison of the prediction and generalization ability of the three gradient descent modes revealed that IBP and BBP outperformed QP. However, among the three algorithms evaluated, BBP appeared to be less biased and more precise judging by it having the least MPE for all properties of steel fiber reinforced concrete investigated. With respect to compressive strength, split tensile strength and slump evaluated by the RMSE, IBP recorded the least RMSE value when compared to BBP. Moreover, no significant difference was found in the predictive ability of IBP and BBP for water

absorption and flexural strength, although, the convergence speed of BBP is more than four times higher than that of IBP. In addition, the CPU time required by the IBP algorithm is only 19.70% of that required by the BBP algorithm.

Figure 7 (a) to (c) showed the correlation between the observed and predicted values for analysis done on all test data set with gradient descent algorithms. It also revealed the model with the highest and lowest predicting ability. The performance of the gradient descent algorithms was further evaluated by R, R^2 and AFV. Judging by the aforementioned statistical parameters, the accuracy of the algorithm in prediction is in the order of IBP > BBP > QP with corresponding values of R, R^2 and AFV of 0.904, 0.82 and 0.892; 0.876, 0.77 and 0.87; 0.852, 0.73 and 0.841 respectively. It can be observed that IBP exhibited the best predicting ability compared with the other two gradient descent algorithms. IBP recorded R value of 0.904 closest to one indicating a good positive relationship and R^2 of 0.82. These results imply a sizable number of the points fell on the regression line with over 80% of the variation observed in the analysis adequately explained. In addition, IBP recorded AFV value of 0.892, which according to Uygur et al. (2014) indicates a better predictive ability of the model when the AFV value is close to one.

3.2.2. ANN training using Levenberg Marquardt

Levenberg Marquardt (LM) another form of back propagation was used in training the neural networks. In order to access the predicting ability of LM, training was done using the same network architecture. In comparison with gradient decent algorithm, LM was observed to have the least average number of epoch while the entire CPU processing duration was close to that of IBP and QP when compared to BBP. Also, LM recorded the least RMSE for mechanical properties such as water absorption (RMSE = 0.549935), split tensile strength (RMSE = 2.200841) and slump (RMSE = 9.169875) when compared with the gradient decent algorithm. Furthermore, linear regression analysis of the performance of LM algorithm, displayed in Fig. 8, revealed R value of 0.89, R^2 value of 0.79 and AFV value of 0.885. In comparison with the gradient descent algorithms results, it was observed that LM was only outperformed by IBP.

3.2.3. ANN training using generic algorithm

GA was also utilized as a training algorithm in the study to ensure that the optimal weight of the network was attained. The selection type used was the absolute top mate selection which has the ability to select the first parent from the most fitted individual by iteration while the subsequent parent is randomly selected. The crossover type was the intermediate crossover which is a linear combination of two parents. A number of runs were carried out with varying population size, crossover rate and mutation rate and the best training set was achieved at 40, 0.8 and 0.1

respectively. The test set was used in determining the termination of training while the evolutionary drive was provided by the training set.

The criteria for accessing the performance of GA were similar to that used for the other algorithms. The average RMSE for the training and testing data set respectively was 0.550651 and 0.531741 for water absorption, 9.064883 and 7.92384 for compressive strength, 1.291409 and 1.947622 for flexural strength, 1.655808 and 1.872817 for split tensile strength and 6.233546 and 5.54189 for slump. The average number of epochs and CPU time attained at the end of training was 20450 and 109 respectively. The study explored linear regression to further access the performance of ANN trained with GA as presented in Fig. 9.

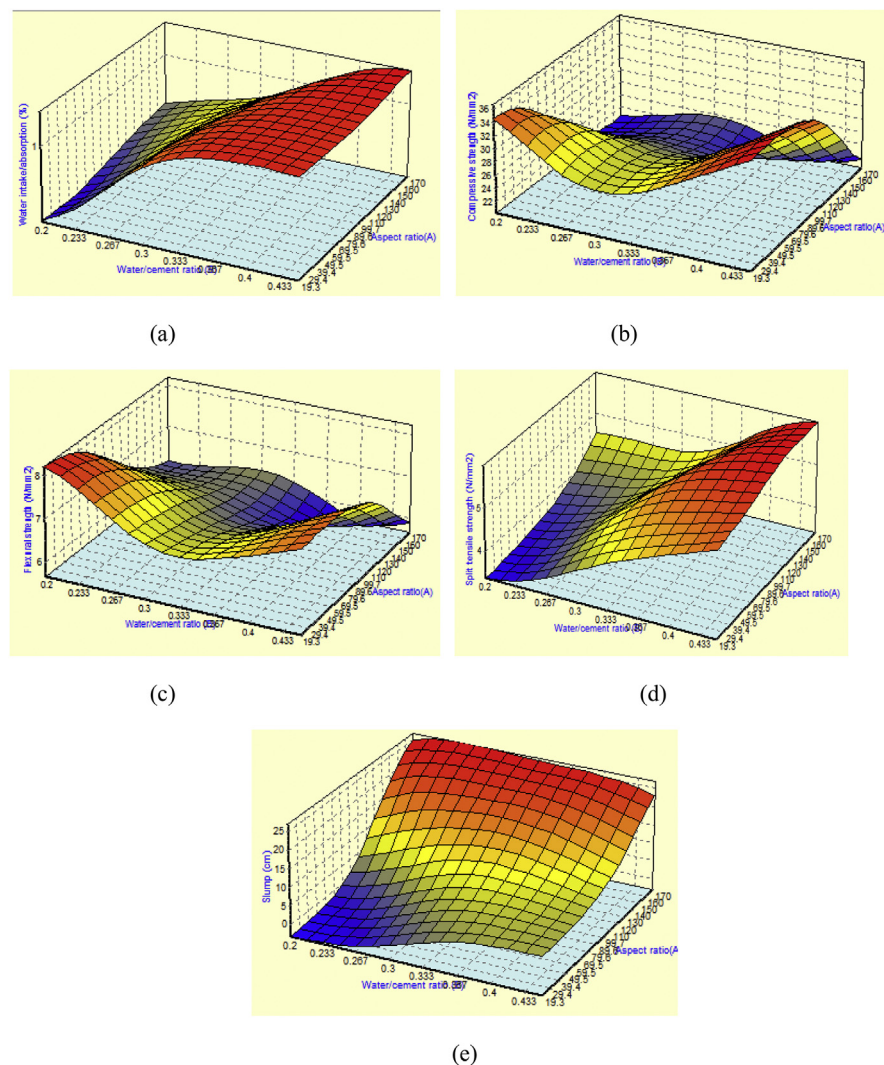


Fig. 10. Response surface plots showing combined effects of variation in water-cement ratio and aspect ratio on (a) water absorption (b) compressive strength (c) flexural strength (d) split tensile strength (e) slump of steel-fibre reinforced concrete.

The R , R^2 and AFV obtained from the plot were 0.97, 0.94 and 0.929 respectively. These results indicated that GA recorded the best predicting ability compared to other algorithms (gradient decent and Levenberg Marquardt algorithm). GA recorded the highest R value of 0.97 (closest to one which a good positive relationship between the predicted and the observed) and R^2 of 0.94. This point of view was supported by the AFV value of 0.929 compared to 0.885 for LM and 0.841–0.892 for the gradient decent algorithms. Based on the statistical measures employed and comparison made for the five training algorithm (IBP, BBP, QP, LM and GA), it can be concluded that GA demonstrate a clear superior predicting ability over the back propagation algorithms such as IBP, BBP, QP and LM. Therefore, genetic algorithm (GA) is recommended for accurate ANN modelling and prediction of the mechanical properties of steel fibre reinforced concrete.

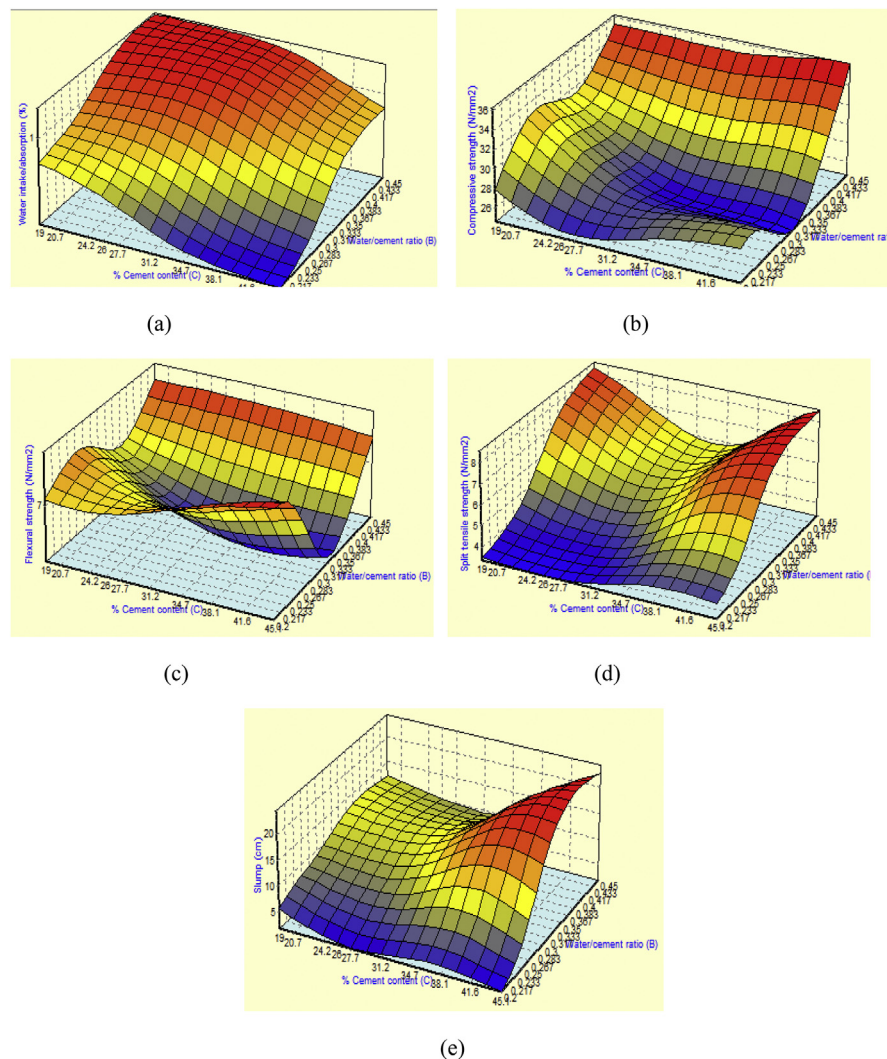


Fig. 11. Response surface plots showing combined effects of variation in cement content and water-cement ratio on (a) water absorption (b) compressive strength (c) flexural strength (d) split tensile strength (e) slump of steel-fibre reinforced concrete.

3.3. Response surface plots for genetic algorithm ANN modeling of SFRC properties

With the aid of the genetic algorithm which recorded the best predictive performance, the response surfaces of experimental results were plotted to study the non-linear relationships among investigated variables such as aspect ratio, water/cement and cement content and observe their effects on mechanical properties of SFRC such as water absorption, compressive strength, flexural strength, split tensile strength and slump. The various response surface plots are displayed in Figs. 10, 11, and 12. Fig. 10 (a) to (e) displays the effect of aspect ratio and the water cement ratio while

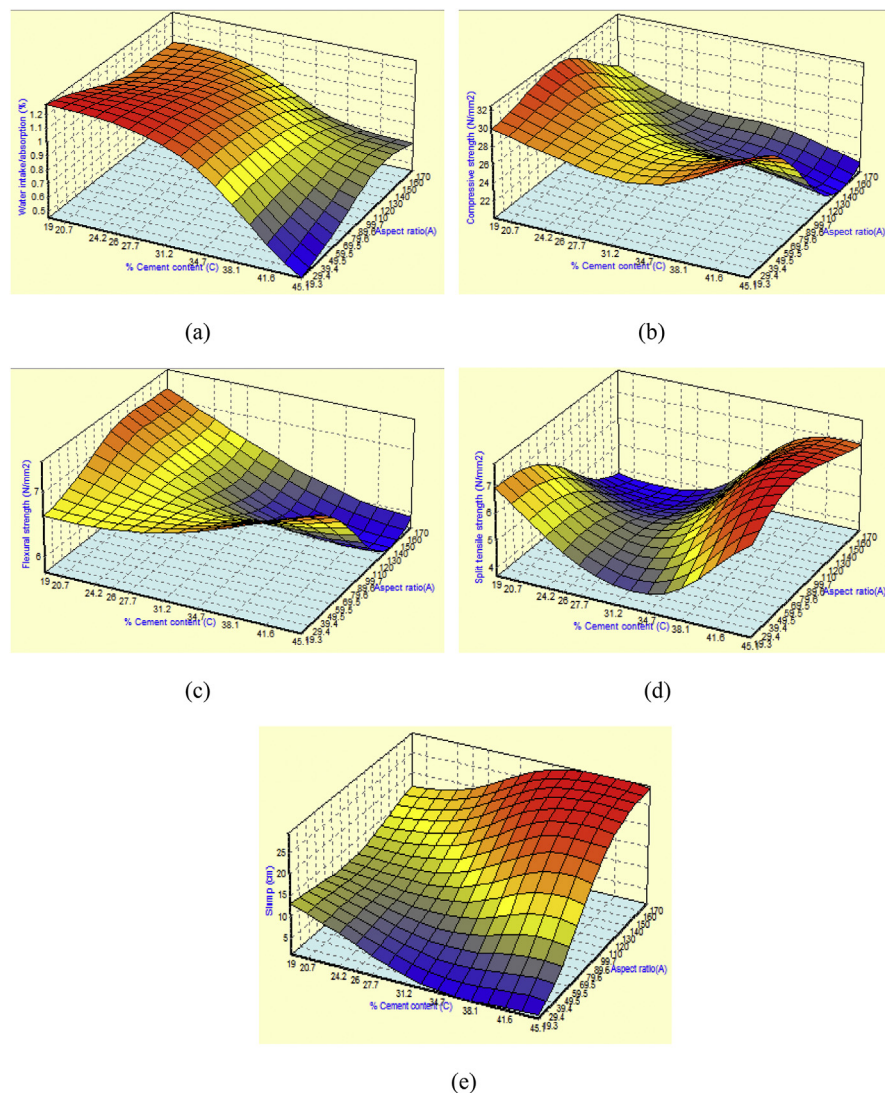


Fig. 12. Response surface plots showing combined effects of variation in cement content and aspect ratio on (a) water absorption (b) compressive strength (c) flexural strength (d) split tensile strength (e) slump of steel-fibre reinforced concrete.

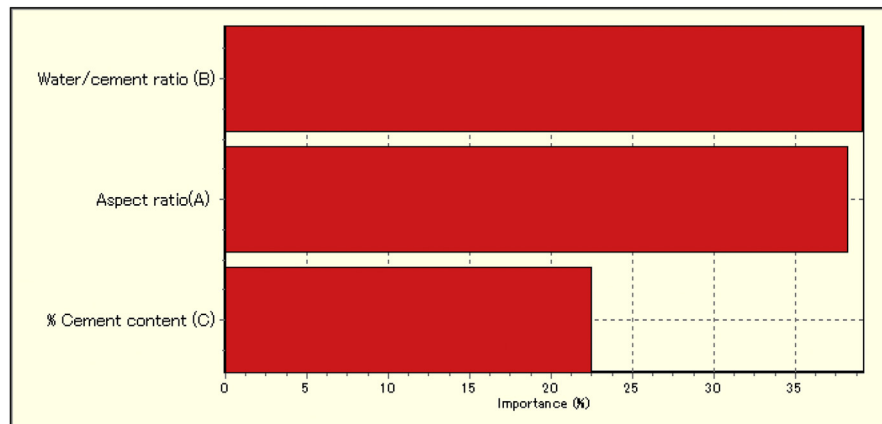


Fig. 13. Importance of independent variables.

Fig. 11 (a) to (e) shows the effect of cement content and aspect ratio and Fig. 12 (a) to (e) displays the effect of water cement ratio and cement content for all responses.

According to Fig. 10 (a), low water absorption was observed at low w/c ratio while the effect of varying aspect ratio seems negligible. The plots of compressive and flexural strength displayed in Fig. 10 (b) to (c) revealed that these strength properties can be enhanced with low values of water cement ratio and moderate aspect ratio. The split tensile strength and slump displayed in Fig. 10 (d) to (e) were observed to increase with increase in water cement ratio and aspect ratio. From Fig. 11 (a), it was observed that low values of water cement ratio and cement content reduces the water absorption of the concrete. With respect to compressive strength, flexural strength, split tensile strength and slump displayed in Fig. 11 (b) to (e), the effect of water cement ratio was significant with highest values obtained at w/c ratio of 0.45 while the cement content seems negligible.

Furthermore, Fig. 12 (a) revealed that increased cement content and reduced aspect ratio will result in reduced water absorption. Conversely, increased cement content and reduced aspect ratio was observed to enhance the compressive and flexural strengths of steel fibre reinforced concrete as shown in Fig. 12 (b) to (c). For split tensile strength, the role of cement content was significant while that of aspect ratio seems marginal as depicted in Fig. 12 (d). Also, the slump was observed to increase with increased aspect ratio and reduced cement content as displayed in Fig. 12 (e).

3.4. Analysis of relative importance of independent variables by genetic algorithm

The relative importance of each independent variable (w/c ratio, aspect ratio and percentage cement content) to the properties investigated in the study is presented in Fig. 13. Water- cement ratio recorded the highest significant contribution of

39.4%, followed by aspect ratio with contribution of 38.1% and cement content with least contribution of 22.5%

4. Conclusion

The study considered the application of artificial neural network (ANN) modeling techniques in predicting the properties of waste tire steel fiber reinforced concrete (SFRC). The effects of three independent variables namely aspect ratio, water-cement ratio and cement content on water absorption, compressive strength, flexural strength, split tensile strength and slump properties of fiber reinforced concrete were investigated. Five algorithms of the ANN were explored for training, namely incremental back propagation (IBP), batch back propagation (BBP), quick propagation (QP), Levenberg–Marquardt back propagation (LM) and genetic algorithm (GA). The predicting ability performance of the ANN training algorithms in descending order was $GA > IBP > LM > BBP > QP$. Genetic algorithm (GA) was selected as the best training algorithm for modeling and predicting the properties of concrete reinforced with fibers obtained from discarded tyre based on statistical measures of performance such as R , R^2 and AFV. The results from our study supports the views of Cortez et al. (2002) who reported that genetic algorithm (GA) evolutionary approach is a better alternative to the back propagation. Therefore, our study concludes that selecting the right training algorithm is vital for successful ANN data modeling and genetic algorithm is highly recommended in ANN modeling to achieve high predictive efficiency.

The major findings from our research are as follows:

- In terms of overall predictive efficiency, GA algorithm is preferable. The order of preference is $GA > IBP > LM > BBP > QP$. Therefore, careful selection of ANN is important for improved ANN predictive efficiency.
- In terms of compressive strength and flexural strength predictions alone, IBP and BBP outperformed GA.
- Water-cement ratio contributes slightly more than aspect ratio and cement content to the overall SFRC mechanical properties. The contribution of water-cement ratio, steel fibre aspect ratio and cement content were 39.4%, 38.1% and 22.5% respectively. Therefore, careful selection of water-cement ratio and steel-fibre aspect ratio is imperative to achieve desirable SFRC with improved mechanical properties.
- Waste tire steel fibres are recommended as a suitable replacement for industrial fibres in steel-fibre reinforced concrete.

Declarations

Author contribution statement

T. F. Awolusi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

O. L. Oke: Conceived and designed the experiments.

O. O. Akinkurolere: Performed the experiments.

A. O. Sojobi: Analyzed and interpreted the data; Wrote the paper.

O. G Alukoa: Contributed reagents, materials, analysis tools or data.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

The authors would like to acknowledge Advanced Chemical Technology Ikeja Lagos, manufacturer of the high range water reducing admixture used in the study. We also express sincere gratitude to Engr. Tawio Abiola of the Department of Chemical Engineering, Cape Peninsula University of Technology, South Africa for his support.

References

- Abd Elaty, M.A.A., Ghazy, M.F., 2016. Evaluation of consistency properties of freshly mixed concrete by cone penetration test. *HBRC Journal* 12, 1–12.
- Aiello, M.A., Leuzzi, F., Gentonze, G., Maffezzoli, A., 2009. Use of steel fibers recovered from waste tyres as reinforcement in concrete: pull-out behaviour, compressive and flexural strength. *Waste Manag.* 29 (6), 1960–1970.

- Alavala, C.R., 2008. Fuzzy Logic and Neural Networks: Basic Concepts and Applications. New Age International, Daryaganj, Delhi.
- Altarazi, s., Ammouri, M., Hijazi, A., 2018. Artificial neural network to evaluate polyvinylchloride composites' properties. *Comput. Mater. Sci.* 153, 1–9.
- BS EN 12350-12352, 2009. Testing Fresh Concrete e Part 2: Slump-test. British Standards Institution, London, United Kingdom.
- BS EN 12390-12393, 2009. Testing Hardened Concrete e Part 3: Compressive Strength of Test Specimens. British Standards Institution, London, United Kingdom.
- BS EN 12390-12395, 2009. Testing Hardened Concrete e Part 5: Flexural Strength of Test Specimens. British Standards Institution, London, United Kingdom.
- BS EN 12390-12396, 2009. Testing Hardened Concrete e Part 6: Tensile Splitting Strength of Test Specimens. British Standards Institution, London, United Kingdom.
- CEALC, 2011. Concrete Mix Design. https://www.cecalc.com/DAS/ConcreteMixDesign/Concrete_Mix_Design_Guide.pdf.
- Centonze, G., Leone, M., Aiello, M.A., 2012. Steel fibers from waste tires as reinforcement in concrete: a mechanical characterization. *Constr. Build. Mater.* 36, 46–57.
- Papakonstantino, Christos G., Tobolski, Matthew J., 2006. Use of waste tire steel beads in Portland cement concrete. *Cement Concr. Res.* 36 (9), 1686–1691.
- Chopra, P., Kumar, R.,S., Kumarb, M., 2015. Artificial neural networks for the prediction of compressive strength of concrete. *Int. J. Appl. Sci. Eng.* 13 (3), 187–204. http://ir.lib.cyut.edu.tw:8080/bitstream/310901800/29740/1/1_036013.pdf.
- CPC-X Software, 2003. Neural Power User Guide. Available: <http://www.geocities.com/neuralpower> https://www2.southeastern.edu/Academics/Faculty/pmcowell/matlab_nnet_help.pdf.
- Ebrahimpour, A., Abd, R.R., Chng, D.H., Basri, M., Salleh, A.B., 2008. A modeling study by response surface methodology and artificial neural network on culture parameters optimization for thermostable lipase production from a newly isolated thermophilic *Geobacillus* sp. strain ARM. *BioMed Central*.
- Fang, J., Wang, S., Zhang, C., 2005. Application of genetic algorithm (GA) trained artificial neural network to identify tomatoes with physiological diseases. *Nat. Sci.* 3, 52–58. <http://www.sciencepub.net/nature/0302/09-fangjunlong.pdf>.

Ghaffari, A., Abdollahi, H., Khoshayand, M.R., Soltani, I.B., Dadgar, A., Rafiee-Tehrani, M., 2006. Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. *Int. J. Pharm.* 327, 126–138.

Ghoushchi, S.J., 2015. Optimization of transportation system based on combined model using artificial neural networks and response surface methodology. *Int. J. Tech. Res. Appl. Speci. Issue* 23, 69–76. <https://pdfs.semanticscholar.org/127d/94453c26cccab679a6a3cae05aa016d587b.pdf>.

Gregory, Marvin Garrick, 2005. Analysis and Testing of Waste Tire Fiber Modified concrete. Master Thesis. Louisiana State University. etd-04112005-154524. https://digitalcommons.lsu.edu/cgi/viewcontent.cgi?article=1216&context=gradschool_theses.

Hacene, B.S.M.A., Ghomari, F., Schoefs, F., Khelidj, A., 2013. Probabilistic modelling of compressive strength of concrete using response surface methodology and neural networks. *Arabian J. Sci. Eng.*

Hameed, R., Turatsinze, A., Duprat, F., Sellier, A., 2009. Metallic fiber reinforced concrete: effect of fiber aspect ratio on the flexural properties. *ARPN J. Eng. Appl. Sci* 4 (5), 67–72. <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.569.6811&rep=rep1&type=pdf>.

Hush, D., Horne, B.G., 1993. Progress in supervised neural networks. *IEEE Signal Process. Mag.* 10, 8–39. <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=180705>.

Lee, S., Oh, J., Cho, J., 2015. Compressive behaviour of fiber – reinforced concrete with end hooked steel fibers. *Materials* 8, 1442–1458.

Li, G., Garrick, G., Eggers, J., Abadie, C., Stubblefield, M.A., Pang, S.-S., 2004. Waste tire fiber modified concrete. *Composites Part B* 35, 305–312.

Maddalena, C., Massimiliano, F., Luca, B., 2014. Comparison of ground waste glass with other supplementary cementitious materials. *Cement Concr. Compos.* 45, 39–45.

Moghaddam, G., Khajeh, M., 2011. Comparison of response surface methodology and artificial neural network in predicting the microwave-assisted extraction procedure to determine zinc in fish muscles. *J. Food Nutr. Sci.* 2, 803–808.

Mohamad, Nizar Bin Abdonasrah, 2011. Toughness of concrete Reinforced with Recycled Tire Steel Fiber. Degree Thesis. Universiti Teknologi Malaysia. <https://books.google.com.hk/books?id=Tu2CnQAACAAJ>.

Muthupriya, P., Subramanian, K., Vishnuram, B.G., 2011. Prediction of compressive strength and durability of high performance concrete by artificial neural networks. *Int. J. Optim. Civil Eng.* 1, 189–209. <http://ijoce.iust.ac.ir/article-1-15-en.html>.

- Onuaguluchi, O., Banthia, N., 2018. Scrap tire steel fiber as a substitute for commercial steel fiber in cement mortar: engineering properties and cost-benefit analyses. *Resour. Conserv. Recycl.* 134, 248–256.
- Pilakoutas, K., Neocleous, K., Tlemat, H., 2004. Reuse of tyre steel fibres as concrete reinforcement. *Eng. Sustain* 157 (3), 131–138.
- Pilkington, J.L., Prestonb, C., Gomesa, R.L., 2014. Comparison of response surface methodology (RSM) and artificial neural networks (ANN) towards efficient extraction of artemisinin from *Artemisia annual*. *Ind. Crop. Prod.* 58, 15–24.
- Plumb, A.P., Rowe, R.C., York, P., Doherty, C., 2002. The effect of experimental design on the modeling of a tablet coating formulation using artificial neural networks. *Eur. J. Pharm. Sci.* 16, 281–288.
- Prusty, J.K., Sanjaya, K.P., 2015. Properties of fresh and hardened concrete using agro-waste as partial replacement of coarse aggregate — a review. *Constr. Build. Mater.* 82, 101–113.
- Sakamoto, H., Matsumoto, K., Kuwahara, A., Hayami, Y., 2005. Acceleration and stabilization techniques for the Levenberg–Marquardt method. *IEICE Trans. Fund.* E88-A, 1971–1978.
- Sawant, R.M., Ghugal, Y.M., Khan, J.A., 2015. Evaluation of split tensile strength of high strength fiber reinforced concrete. *Int. J. Tech. Res. Appl.* 3 (6), 243–247 e-ISSN: 2320-8163. https://www.researchgate.net/profile/Rajmahendra_Sawant/publication/309292318_EVALUATION_OF_SPLIT_TENSILE_STRENGTH_OF_HIGH_STRENGTH_FIBER_REINFORCED_CONCRETE/links/58088ff308ae07cbaa544910/EVALUATION-OF-SPLIT-TENSILE-STRENGTH-OF-HIGH-STRENGTH-FIBER-REINFORCED-CONCRETE.pdf.
- Shihani, N., Kumbhar, B.K., Kulshreshtha, M., 2006. Modeling of extrusion process using response surface methodology and artificial neural networks. *J. Eng. Sci. Technol.* 1 (1), 31–40. In: https://www.researchgate.net/profile/Baburao_Kumbhar2/publication/49592668_Modeling_of_extrusion_process_using_response_surface_methodology_and_artificial_neural_networks/links/00463538d5c444ca4d000000/Modeling-of-extrusion-process-using-response-surface-methodology-and-artificial-neural-networks.pdf.
- Sojobi, A.O., Aladegboye, O.J., Awolusi, T.F., 2018. Green interlocking paving units. *Constr. Build. Mater.* 173 (2018), 600–614. <https://doi.org/10.1016/j.conbuildmat.2018.04.061>.
- Stanley, C., 2011. The use and abuse of slump test for measuring the workability of concrete. In: 36th Conference on Our World in Concrete & Structures

Singapore, August 14–16, 2011. <https://pdfs.semanticscholar.org/b19d/ecf3a1a5ec4062fce8f482f2f1244ff20cd8.pdf>.

Syaidathul, Izni, 2012. Mechanical Properties of Recycled Steel Fiber in concrete. Technical report. Faculty of Civil Engineering, University of Technology, Malaysia. <http://people.utm.my/iznisyahrizal/files/2013/02/Technical-Report-1.pdf>.

Thomas, B.S., Gupta, R.C., Kalla, P., Cseteneyi, L., 2014. Strength, abrasion and permeation characteristics of cement concrete containing waste rubber fine aggregates. *Constr. Build. Mater.* 59, 204–212.

Torre, A., Garcia, F., Moromi, I., Espinoza, P., Acuña, L., 2015. Prediction of compression strength of high performance concrete using artificial neural networks. In: VII International Congress of Engineering Physics IOP Publishing Journal of Physics: Conference Series 582.

Uygur, I., Cicek, A., Toklu, E., Kara, R., Saridemir, S., 2014. Fatigue life predictions of metal matrix composites using artificial neural networks. *Arch. Metall. Mater.* 59 (1), 98–103.

Yang, I.H., Joh, C., Kim, B.S., 2011. The Twelfth East Asia-Pacific conference on structural engineering and construction flexural strength of ultra high strength concrete beams reinforced with steel fibers. *Proc. Eng.* 14, 793–796.

Yao, W., Li, J., Wu, K., 2003. Mechanical properties of hybrid fiber-reinforced concrete at low fiber volume fraction. *Cement Concr. Res.* 33, 27–30.

Zobel, C.W., Cook, D.F., 2011. Evaluation of neural network variable influence measures for process control. *Eng. Appl. Artif. Intell.* 24, 803–812.