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Article

# Comparison of Response Surface Methodology and Hybrid-Training Approach of Artificial Neural Network in Modeling the Properties of Concrete Containing Steel Fiber Extracted from Waste Tires

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**Abstract:** The study presents a comparative approach between response surface methodology (RSM) and hybridized, genetic algorithm artificial neural network (GA-ANN) in predicting the water absorption, compressive strength, flexural strength split tensile strength and slump for steel fiber reinforced concrete. The effect of process variables such as aspect ratio, water cement ratio and cement content were investigated using the central composite design of response surface methodology. This same experimental design was used in training the hybrid-training approach of artificial neural network. The predicting ability of both methodologies were compared using the root mean sqaured error (RMSE), mean absolute error (MAE), model predictive error (MPE) and absolute average deviation (AAD). The RSM model was found more accurate in prediction compared to hybrid GA-ANN.

**Keywords:** Response Surface Methodology; Hybrid; Genetic Algorithm Artificial Neural Network; Concrete; Flexural Strength; Steel Fibre Reinforced Concrete; Civil Engineering

## 1. Introduction

The annual global generation of end-of-life tyres, which is about 1.4 billion units, is estimated to reach 2.5 billion units in 2032 based on a maximum lifespan of 10 years for vehicular tyres [1,2]. The bulkiness, shear volume and resilience of waste tyres makes the case of recycling their principal components indispensable in order to reduce the associated environmental hazards attributed to illegal burning of these reusable wastes. The huge quantity of this waste has arose the interest of many researchers ([3–9]. The low recycling rates reported in some developed countries and most developing countries are attributable to absence of regulatory framework for collection, disposal and recycling, inefficient recycling process and perceived low economic value of the waste products [10]. While the rubber components have been extensively researched, the steel fiber component has not received considerable attention [11].

In addition, the lack of specific mix design for steel fiber usage in concrete limits their construction applications and makes optimization of the components of steel fiber reinforced concrete very essential [11]. Optimization helps to improve the mechanical properties of steel fiber reinforced (SFRC), fast-track design process, reduce laboratory trials and ensures reliability of the SFRC product which is essential in concrete structures and the fast-paced engineering construction. RSM can also be used to fine-tune the SFRC components mix to achieve desirable properties based on specific, target applications. A quantitative characterization of the efficiency of steel fibers extracted from waste tires can provide a guide on the use of steel fibers for durable, cost effective mix design. The study is conducted to inform early decision on the fresh and harden properties of concrete reinforced with steel fiber extracted from waste tires due to the

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paucity of literature on steel fiber reinforced concrete, and its slow uptake by the construction industry. The application of statistical tools like RSM provides useful information that can be used to refine the design criteria and specification for better performance of a system. Another advantage of statistical tools is the ability to perform quick prediction once fitted into a function [12]. Response Surface Methodology (RSM) is a valuable tool for designing experiment, building of models and optimization of search conditions to provide better outputs by fitting effect factors to quadratic functions [13–17].

Hybridization can be achieved by combining intelligent techniques such as fuzzy logic, neural networks, genetic algorithm and expert system. When applied to a wide range of real life problems, they were found to be effectiveness since the limitation experience of one technique can be overcome by the other technique [18–20]. Most intelligent technique has the ability to learn from examples which makes them suitable for many applications. Genetic algorithm is a form of artificial intelligence techniques that imitates the principles of biological evolution. This algorithm involves a general search approach that is stochastic in nature. In this approach new population of individuals are generated from the existing populations. GA computes a new population by applying stochastic operators such as selection, crossover and mutation for an initially random population. The searching feature present in GA is population driven and not trajectory driven like the gradient descent and LM algorithm [16,21]. The hybridized genetic algorithm of artificial neural network (ANN) is another approach that can be used for refining the design criteria for enhanced system performance. According to Fang et al. [22] the genetic algorithm employs a evolutional search approach in order to obtain an optimal solution which differs from the one point at a time approach employed in the gradient decent and Levenberg Marquardt algorithms. When genetic algorithm is limited in fine tuning local search within a problem it is usually integrated with a gradient decent algorithm. The process is referred to as hybrid-training approach. The application of the hybrid-training approach enables the weakness of one algorithm to be compensated for by the other [21].

The investigation is aimed at developing and comparing the performance RSM and ANN-GA models in predicting the properties of fiber reinforced concrete. Both the fresh and hardened properties of steel fiber reinforced concrete were explored in the study (water absorption, compressive strength, flexural strength, split tensile strength and slump). The effect of variables such as aspect ratio, water cement ratio and cement content were utilized for this process. The derived models were then compared using Root mean sqaured error (RMSE), mean absolute error (MAE), Model predictive error (MPE) and absolute average deviation (AAD) in order to identify the most suitable technique for predicting the properties of fiber reinforced concrete.

### 1.1 Comparison of ANN and RSM in literature

In the last few decades ago, there have being increasing interest by researchers to investigate the suitability RSM and ANN modeling techniques in practical problems as presented in Table 1. Hacene et al. [23] studied probabilistic modeling of compressive strength of concrete using response surface methodology and neural networks. They concluded that the application of either RSM or ANN modeling techniques is practical approach with a promising future depending on the objectives to be achieved. Esfahanian et al. [24] modeled and optimized ethanol fermentation using saccharomyces cerevisiae. They observed that the prediction by ANN was slightly more precise than RSM based on experimental data. Pikington et al. [25] compared the performance of both techniques on the extraction of artemisinin from Artemisia annua. They appraised the models through the coefficient of determination ($R^2$) and the absolute average deviation (AAD) which showed that the ANN was superior to the RSM model in predicting artemisinin recovery.

Maran et al. [26] applied ANN and RSM in modeling and predictions mass transfer parameters during osmotic dehydration of Carica papaya using standard error of prediction, root mean square error, mean absolute error, coefficient of determination and model prediction error The results showed that properly trained ANN model is found to be more accurate in prediction as compared to RSM model. Desai

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et al [16] accessed the performance of ANN-GA and RSM in fermentation media optimization. The ANN-GA was observed to have a better predicting and generalization capacity than the RSM. Bourquin et al. [27] explored the applicability of the ANN modeling techniques in studying the data set with nonlinear relationship of galenical study on a solid dosage form. This was done using the degree of data fitting and predicting abilities of the developed models. Better results were achieved for the model using ANN methodology with regard to data fitting and predicting ability. Moghaddam and Khajeh [28] compared the ability of RSM and ANN in Microwave-Assisted Extraction Procedure to Determine Zinc in Fish Muscles. The predictions by ANN were observed to be more accurate when compared to that of the ANN.

Ravikumar et al. [29] investigated the suitability of RSM and ANN in the modeling and optimization of distillery spent wash treatment with Phormidium valderianum. The predictions obtained for both model were close to experimental values. However ANN revealed reasonable performance over RSM.

Table 1: Comparison of ANN and RSM in literature

| Authors | Process | Results | | Remarks |
|---|---|---|---|---|
| | | ANN | RSM | Superior |
| Hacene et al. [23] | Concrete compressive strength | $R^2$ = 0.959 | $R^2$ = 0.948 | ANN |
| Pikington et al., [25] | Drug extraction | COD ($R^2$) = 0.991<br>AAD = 1.37% | COD ($R^2$) = 0.903<br>AAD = 4.57% | ANN |
| Esfahanian et al. [24] | Ethanol fermentation | $R^2$ = 0.996<br>$R^2$ =0.997 | $R^2$ = 0.985<br>$R^2$ = 0.993 | ANN |
| Bourquin et al. [27] | Pharmaceutical tablet development | $R^2$ = 0.708<br>$R^2$ =0.849 | $R^2$ = 0.997<br>$R^2$ =0.998 | ANN |
| Ravikumar et al. [29] | Distillery spent wash treatment | $R^2$ =0.999 | $R^2$ = 0.9830 | ANN |
| Lakshminarayanan & Balasubramanian [30] | Weld quality | $R^2$ =0.9918<br>MPE = 0.259 | $R^2$ = 0.970<br>MPE = 0.770 | ANN |
| Desai et al. (2008)[16] | Fermentation media optimization | $R^2$ =0.99<br>RMSE=0.11 | $R^2$ =0.93<br>RMSE=0.31 | ANN |

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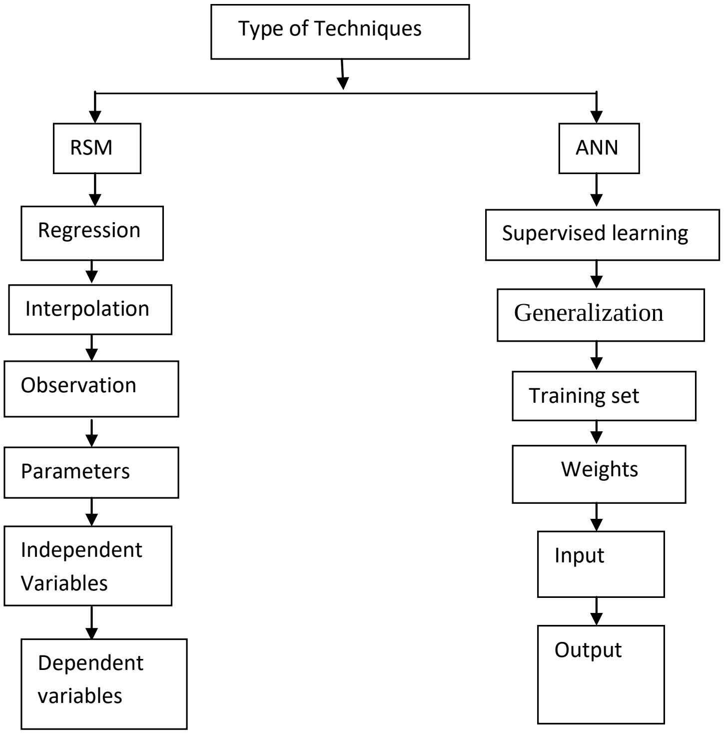


Figure 1: Comparison between RSM and ANN process

**2. Materials and Methods**

The materials used in the study include the grade 42.5 ordinary portland cement, lime stone powder as filler, steel fiber, high range water reducing admixture, river sand, granite and potable water. Details of the mix proportion and procedure have published in our earlier study [31]. The experimental design often plays a major role in determining the total number of experiment required during investigation. The study utilized the central composite design in determining the required number of experiments. According to Pilkington et al. [25] the central composite rotatable design provides an opportunity for introducing axial points into the experimental design. The central composite design is generally used to ensure accurate prediction when examining larger spread conditions in which the complexity of model is not known by providing five levels for each process variable as presented in Figure 2a. The process variables considered in the study at different levels are given in both actual and coded terms as follows:

- Aspect ratio (A): 170(+1.68979), 140(+1),95(0), 50(-1), 19.32(-1.68979)
- Water cement ratio(B): 0.45(+1.68979), 0.40(+1),0.33(0),0.25(-1),0.2(-1.68979)
- Cement (C): 45.1(+1.68979), 40(+1), 32.5(0),25(-1), 19.(-1.68979)

**2.1 Design of artificial neural network**

Previous researchers have highlighted the disadvantage of using the gradient descent algorithm in ANN training because of the likelihood of being caught in a local minimum error function and have proposed an evolutionary approach known as genetic algorithm (GA) however the inability of GA to provide to fine tune local search has brought about the hybridization of GA and back propagation. This approach has been recommended for ANN training [21]. The study obtained a supervised ANN in predicting the five properties of steel fiber reinforced concrete investigated using the hybridized genetic algorithm. The genetic algorithm with incremental back propagation was used to achieve the hybridized genetic algorithm. The incremental back propagation is a form of the gradient decent algorithm. The experimental data obtained from the central composite design of RSM were divided into two set namely

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the training set and testing set. The training set contained fifteen experimental data while the testing set contained five experimental data.

The general ANN architecture consists of three layers which are the input, hidden and output layers. The number of neurons in both the input and output layers are usually determined by process variables and the investigated responses respectively. The number of neurons in the hidden layer was determined by trial and error process. This was done to minimize the deviation of predictions from experimental data. The ANN architecture for the study is presented in Figure 2b. From this Figure it can be observed that a single hidden layer with fifteen neurons was used while the number of neurons in the input and output layers corresponds with the process variables (Aspect ratio, Water cement ratio and Cement content) for the five properties investigated (water absorption, compressive strength, flexural strength, split tensile strength and slump). Further increase in the neurons of the hidden layer presents the possibility of over fitting the ANN. The transfer function of the network for both the hidden and output layers was sigmoidal. The weight is an adjustable quantity that is associated with the connection of neurons. The scaled input data are introduced into the hidden layer by the neurons in the input layer through weights. These weights are the thin lines shown in Figure 2b connecting successive layers.

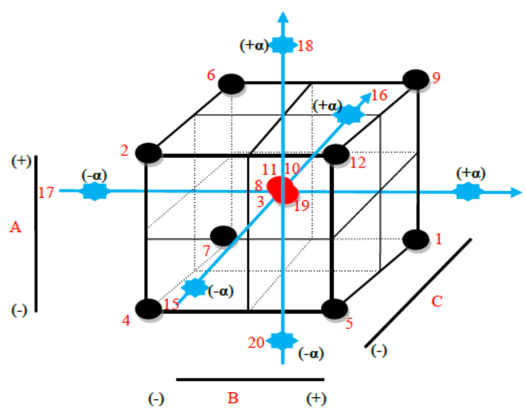


Figure 2a: The RSM architecture

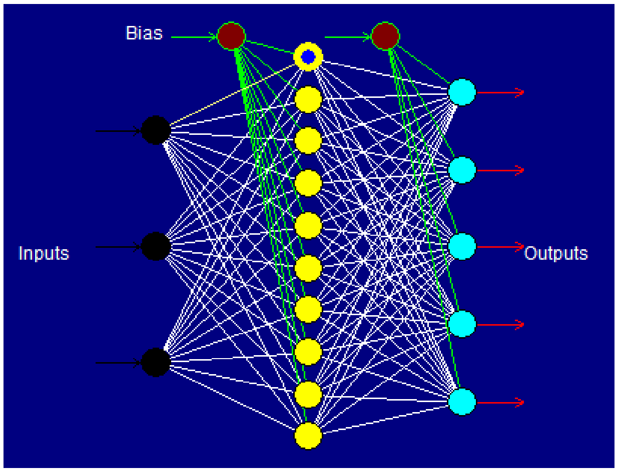


Figure 2b: The ANN architecture

For this study the performance of both techniques was evaluated using the following error functions; Root mean sqared error (RMSE), Mean absolute error (MAE), Model predictive error (MPE) and Absolute average deviation (AAD). The equations representing each error function is presented by 1 to 4 (Maran et al., 2013; Pikington et al., 2014).

$$RMSE = \frac{\sum_{i=1}^{n}(R_{ie} - R_{ip})^2}{n} \quad \ldots 1$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|R_{ie} - R_{ip}| \ldots 2$$

$$MPE\ (\%) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{R_{ie} - R_{ip}}{R_{ip}}\right| \quad \ldots 3$$

$$AAD = \left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{R_{ip} - R_{ie}}{R_{ie}}\right)\right) \times 100 \qquad \ldots 4$$

Where n represents the number of experimental runs, $R_{ie}$ is the ith values experimental and $R_{ip}$ ith value predicted.

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## 3. Results

### 3.1 Performance of RSM and ANN models

The predicting ability of RSM and ANN- GA were accessed in the study. The aforementioned techniques predicted all properties investigated at twenty experimental points. Details of this is presented in Figure 3(a - e). This Figure represents the experimental versus predicted RSM and ANN values for Water absorption (R1), Compressive strength (R2), Flexural strength (R3), Split tensile strength (R4) and Slump (R5) are presented in Figures 3(a - e) respectively. These Figures shows the predicted RSM values were closer to the experimental data than the predicted ANN – GA values. The root mean sqaure error (RMSE), mean absolute error (MAE), Model predictive error (MPE) and absolute average deviation (AAD) is presented in Table 2 and Figure 4 were used to compare the experimental values with RSM and ANN-GA. Although both techniques were observed to predict the responses to a certain level of accuracy as presented in Table 2, however for all responses the RSM was able to provide a better prediction than ANN-GA.

The RSM and ANN- GA values obtained for RMSE, MAE, MPE and AAD for water absorption are 0.105 versus 0.417, 0.079 versus 0.1950, 0.401 versus 2.4389 and 0.065 versus 0.1245 respectively. For compressive strength the values of RMSE, MAE, MPE and AAD obtained for RSM and ANN-GA are 1.577 versus 7.0922, 1.409 versus 2.3874, 0.262 versus 2.3874 and 0.022 versus 0.6329 respectively. For Flexural strength the values of RMSE, MAE, MPE and AAD obtained for RSM and ANN are 0.639 versus 1.8389, 0.274 versus 0.4696, 0.238 versus 0.3836 and 0.078 versus 0.3105 respectively. For Split tensile strength the values of RMSE, MAE, MPE and AAD obtained for RSM and ANN are 0.312 versus 1.0558, 0.265 versus 0.4975, 0.231 versus 0.3836 and 0.0132 versus 0.5772 respectively. For slump the values of RMSE, MAE, MPE and AAD obtained for RSM and ANN -GA are 1.236 versus 2.4054, 1.007 versus 1.1439, 0.497 versus 0.6764 and 0.134 versus 0.6790 respectively.

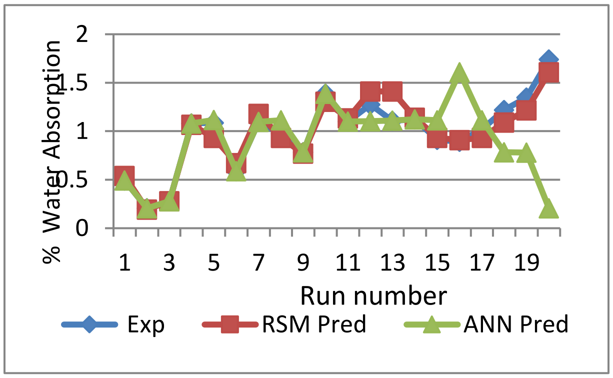



Figure 3a: RSM and ANN- GA comparison for R1

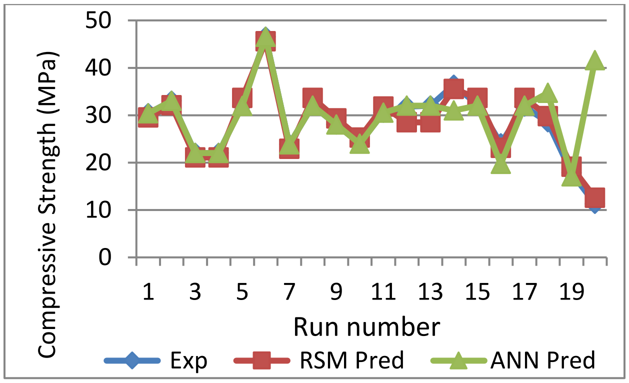
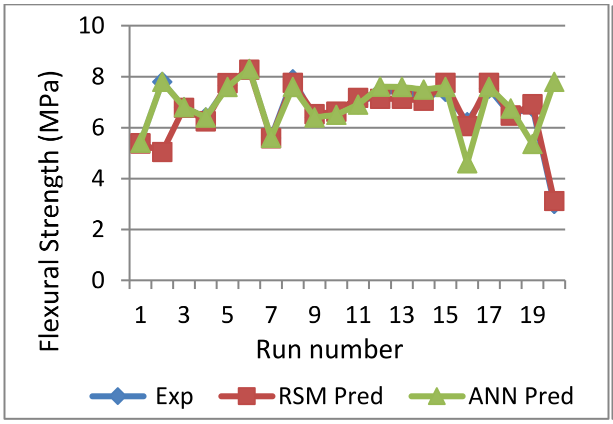



Figure 3b: RSM and ANN- GA comparison for R2



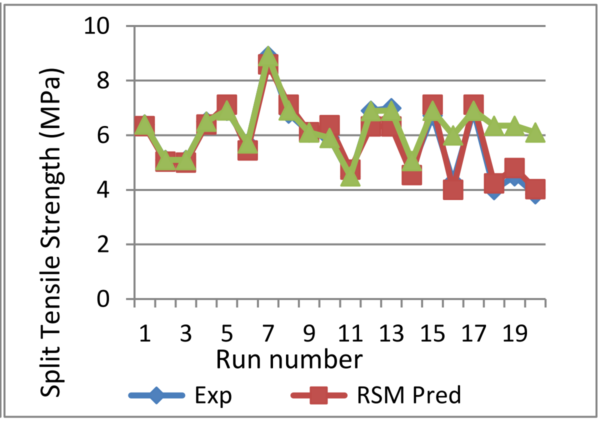



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Figure 3c: RSM and ANN-GA comparison for R3

Figure 3d: RSM and ANN –GA comparison for R4

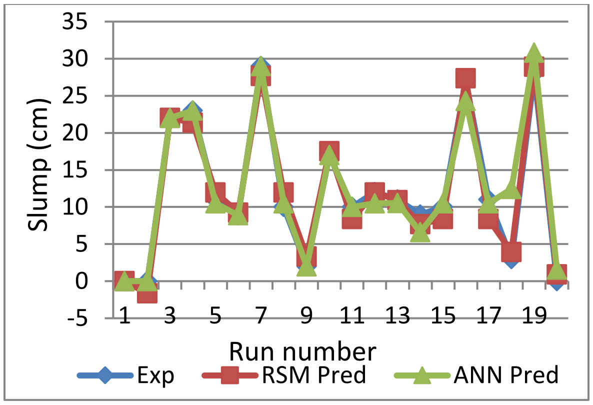


Figure 3e: RSM and ANN –GA comparison for R5

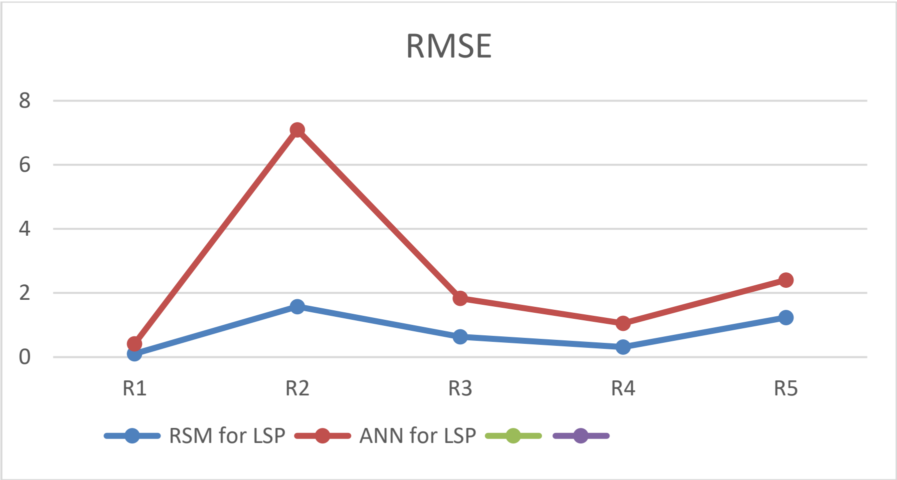


Figure 4a: Plot of the Root mean sqaure error for all response

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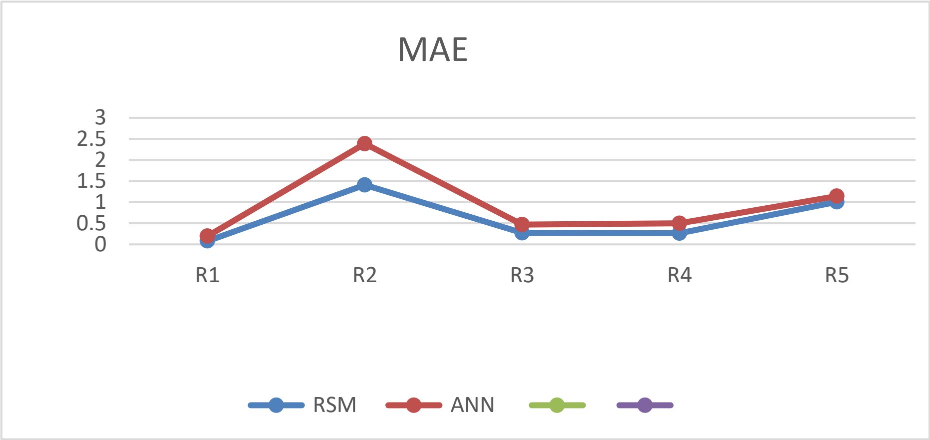


Figure 4b: Plot of the mean absolute error for all response

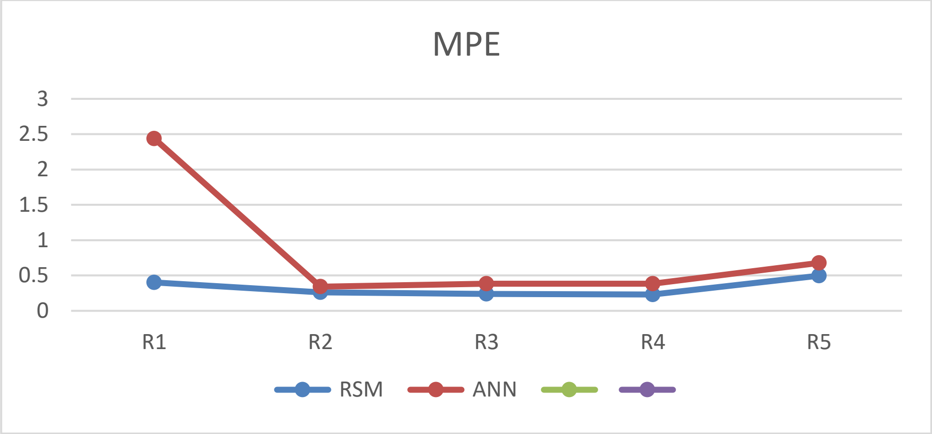


Figure 4c: Plot of the model prediction error for all response

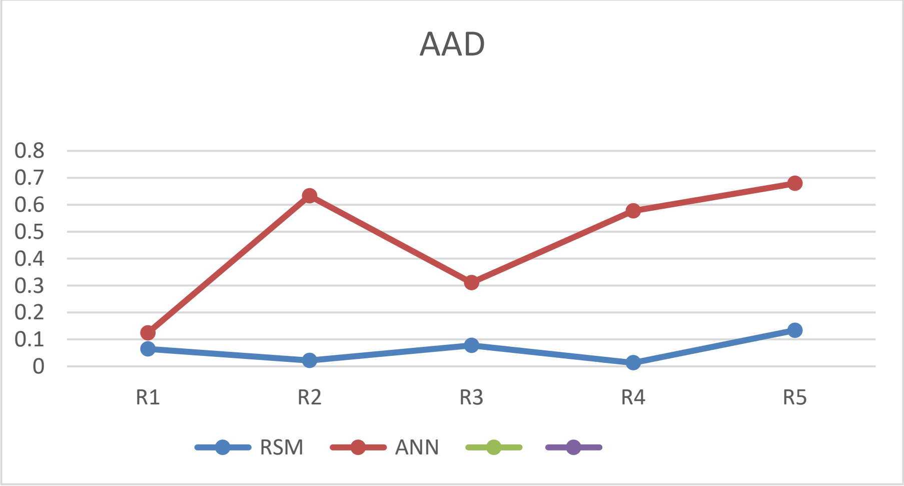


Figure 4d: Plot of the absolute average deviation for all response

Table 2: Evaluation of the ANN-GA and RSM model

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| Central composite design | | | |
|---|---|---|---|
| Parameters | RSM | ANN | Investigated Property |
| RMSE | 0.105 | 0.4170 | Water Absorption |
| MAE | 0.079 | 0.1950 | |
| MPE | 0.401 | 2.4389 | |
| AAD | 0.065 | 0.1245 | |
| RMSE | 1.577 | 7.0922 | Compressive Stength |
| MAE | 1.409 | 2.3874 | |
| MPE | 0.262 | 0.3416 | |
| AAD | 0.022 | 0.6329 | |
| RMSE | 0.639 | 1.8389 | Flexural Strength |
| MAE | 0.274 | 0.4696 | |
| MPE | 0.238 | 0.3836 | |
| AAD | 0.078 | 0.3105 | |
| RMSE | 0.312 | 1.0558 | Split Tensile Strength |
| MAE | 0.265 | 0.4975 | |
| MPE | 0.231 | 0.3836 | |
| AAD | 0.0132 | 0.5772 | |
| RMSE | 1.236 | 2.4054 | Slump |
| MAE | 1.007 | 1.1439 | |
| MPE | 0.497 | 0.6764 | |
| AAD | 0.134 | 0.6790 | |

## 4. Discussion

### 4.1 Derived model using RSM

From the analysis of variance (ANOVA) it was observed that the quadratic model containing a few cubic terms predicted the investigated properties of steel fiber reinforced concrete. The second order model for water absorption, compressive strength, flexural strength, split tensile strength and slump are given by equations 5 to 9 with a coefficient of determination of 0.86, 0.95, 0.98, 0.93 and 0.98 respectively. The equation 5 to 9 gives the regression coefficients for the main, interaction, quadratic and cubic terms [31].

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$Water\ Absorption\ (R1) = +0.16 + 0.062A - 0.14B - 0.14C + 0.098AB + 0.1AC + 0.17BC - 0.036A^2 + 0.047B^2 - 0.082C^2 + 0.14ABC + 0.25A^2B + 0.25A^2C$ ……….. (5)

$Compressive\ strength\ (R2) = +32.99 - 1.15A - 4.46B + 6.24C - 1.24AC - 5.04BC + 0.19B^2 - 5.11C^2 + 0.67B^2C - 1.93BC^2$ …………. …….. (6)

$Flexural\ strength\ (R3) = +6.82 + 0.24A + 1.23B + 1.17C - 0.19AB - 0.38AC - 0.80BC - 1.01B^2 - 0.37C^2 - 0.69B^2C - 1.04BC^2$ …………. …….. (7)

$Split\ tensile\ (R4) = 4.65 + 0.095A + 1.22B + 1.07C + 0.21AB + 0.016AC + 0.16BC - 0.25A^2 - 0.56B^2 - 0.42C^2 + 0.75ABC - 1.54A^2B - 0.71A^2C$ …………. …….. (8)

$Slump\ (R5) = +10.95 - 0.54A + 8.62B + 7.73C - 1.62AB + 5.88AC + 2.63BC - 4.04A^2 + 2.27B^2 + 1.74C^2 - 4.88ABC - 6.25A^2B - 6.85A^2C$ …………. …….. (9)

**4.2 Derived model using ANN- GA**

The generalization capability of ANN –GA was assessed by carrying out a linear regression on the test data set. The experimental and predicted values are presented in Figure 5. The model coefficient of determination ($R^2$) and the absolute fraction of variance (AFV) obtained from the plot were 0.94 and 0.929 respectively. The value of $R^2$ and AFV obtained signifies a close relationship between the experimental values and the predicted values. Atoyebi et al. [32] has identified that the closer this value is to one (1) the better is the predicting ability of the obtained model [32].

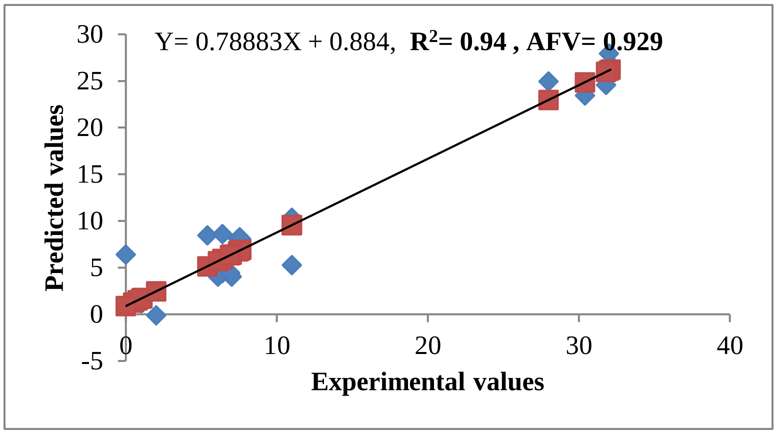


Figure 5.Comparison of Experimental values (red) with predicted values (blue). The straight line represents the linear regression [33].

**4.3 Mean effect Plot**

Figure 6 to 8 presents the the main effect plot for the three process variables. These plots are used to understand the effect of linear terms on interested response [34]. The main effect plot for variable A which represents the aspect ratio of steel fiber is displayed in Figure 6 a to e. From Figure 6a, b and e there was no obvious trend for water absorption, compressive strength and slump with respect to changes in aspect ratio. However the least water absorption, highest compressive and reduced slump was observed with an aspect ratio of 140. The split tensile strengths was observed to increase with increase in aspect ratio upto 140 which implies the maximum aspect ratio 140 required for improved split tensile strengtgh is 140. The flexural strength (Figure 6c) was observed to be constant with aspect ratio between 19 and 50, while further increase in aspect ratio led to a decrease in flexural strength.

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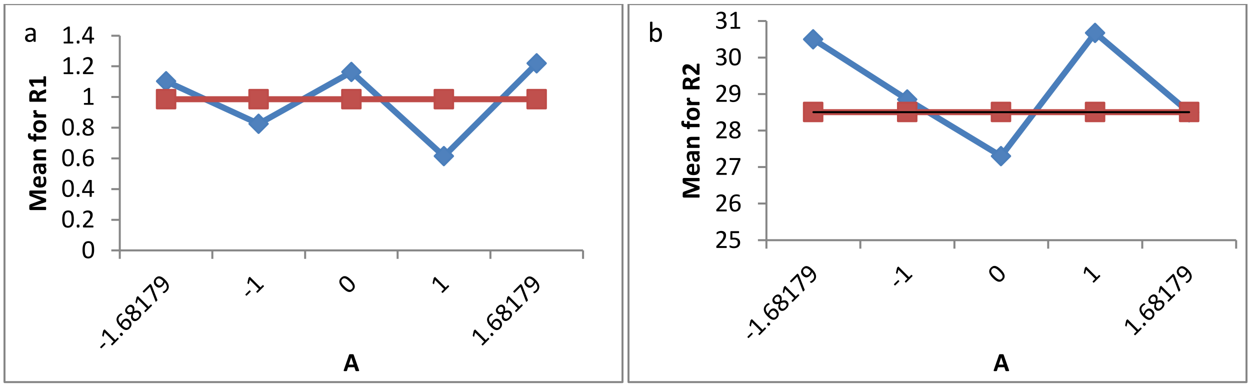
Figure 7 presents the main effect plot for water cement ratio (variable B). From Figure 7a, b and c it was observed that low water absorption, high compressive and flexural strengths could be achieved with water cemet ratio of 0.25. The split tensile strength (Figure 7d) was observed to increase up to water cement ratio of 0.4 whereby further increase in water cement ratio decreases the split tensile strength. From Figure 7e it could be observed that reasonable slump for good workabilty can be achieved with water cement ratio 0.25 and 0.33. Figure 8 presents the main effect plot for variable C (cement). From Figure 8a it was observed that with cement content of 32.5% the lowest water absorption can be achieved. From Figure 8b and c the highest compressive and flexural strengths can be achieved with cement content of 40%. For split tensile strength no clear trend was observed however lower cement content seem to favour split tensile strength (Figure 8d). Figure 8e presents the effect of variable C (cement) on slump. The slump was observed to have increased with increasing cement content which is in agreement with Marar and Eren (2011)[35]. According to the gradient of the main effect plots it was generally observed that the process variable B (water cement ratio) had more influence on the responses when compared to the other two variables (Aspect ratio and cement content). This assertion is supported by the analysis of relative importance of process variables carried out using the hybridized genetic algorithm of ANN as presented in Figure 9. From figure 9 it could be observed that the water cement ratio has the most significant influence on the responses followed by the aspect ratio and lastly the cement content. This observation collaborate the recommendations of Mindess (2003)[36] who identified with water cement ratio as playing a primary role in strength increase while the presence of fibers provides modest increase in strength. Rostamiyan et al. [34] observed that the presence of fibers improves mechanical properties and reduces crack propagation of composite materials. However Simoes et al. [37] has indentified that the precences of fibers in concrete matrix reduces homogeneity and increases the porosity of the concrete. Claisse et al. [38] indentified that the more open the pore sizes of a concrete, the more vulnerable the materials is to degradation caused by penerating substances. This substances which are mostly liquid moves from the surronding environment into the concrete matrix and may cause irreparable damage to the material. The rate of water absoprtion is closely related to the sizes of the pores in the concrete. Therefore the study has provided regression models that could help in proportioning the consistuent of steel fiber reinforced concrete with minimum water absorption, resonable slump and improved mechanical properties.



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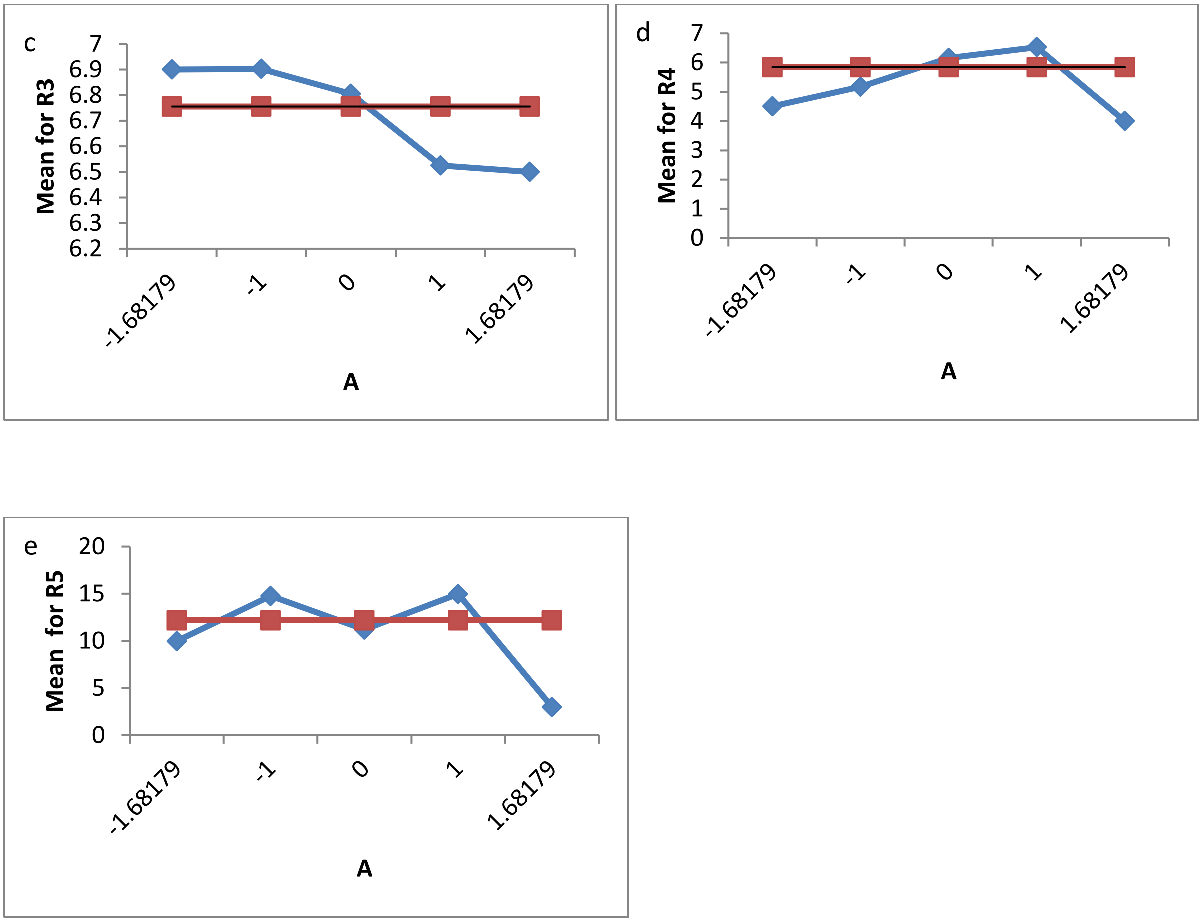
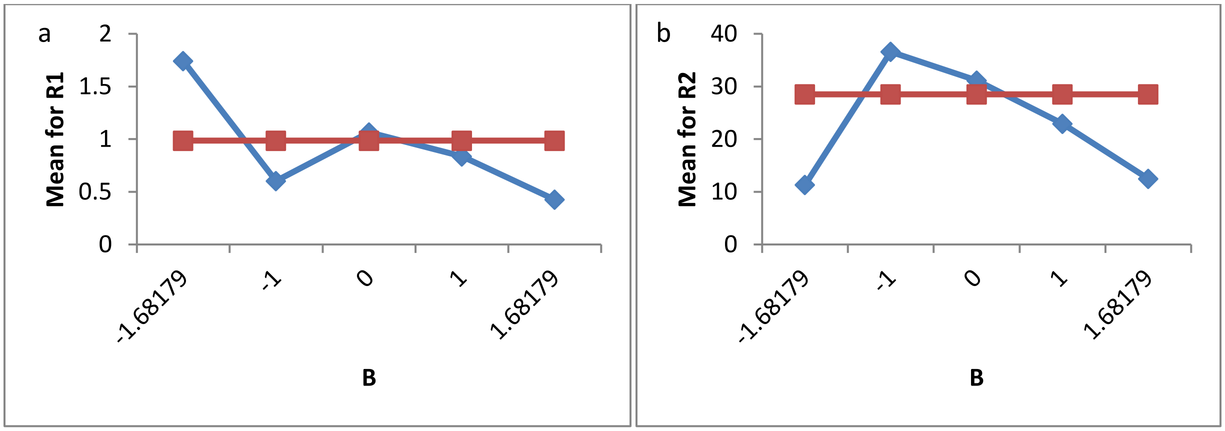



Figure 6: Main effect plot of factor A on all responses



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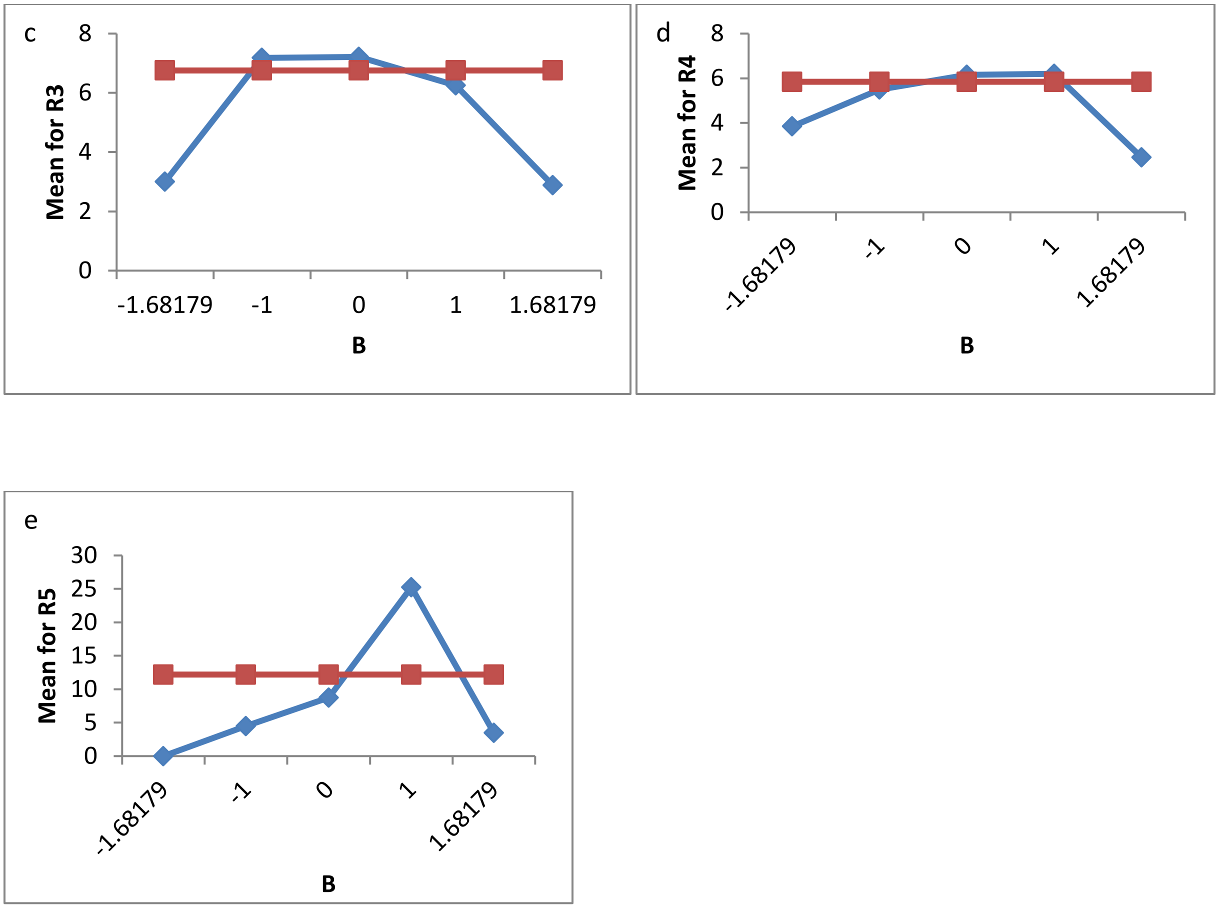
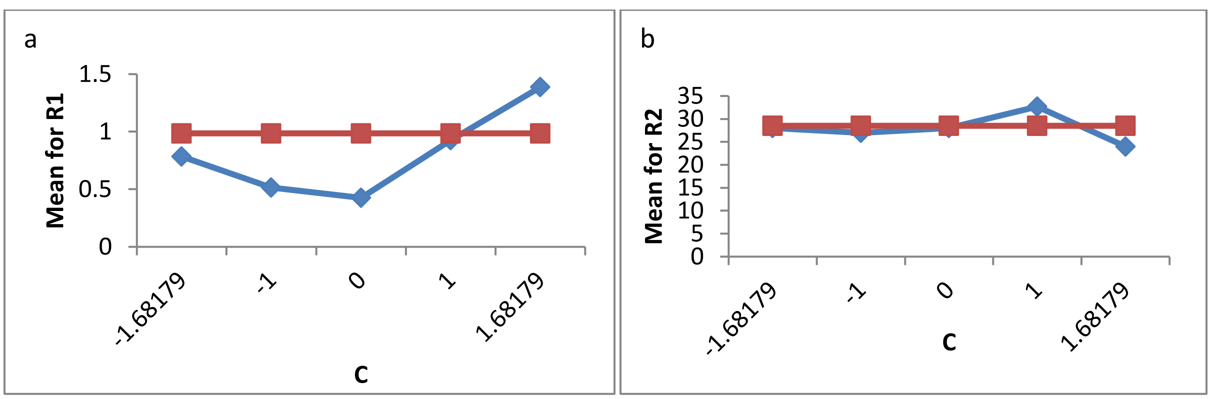



Figure 7: Main effect plot of factor B on all responses



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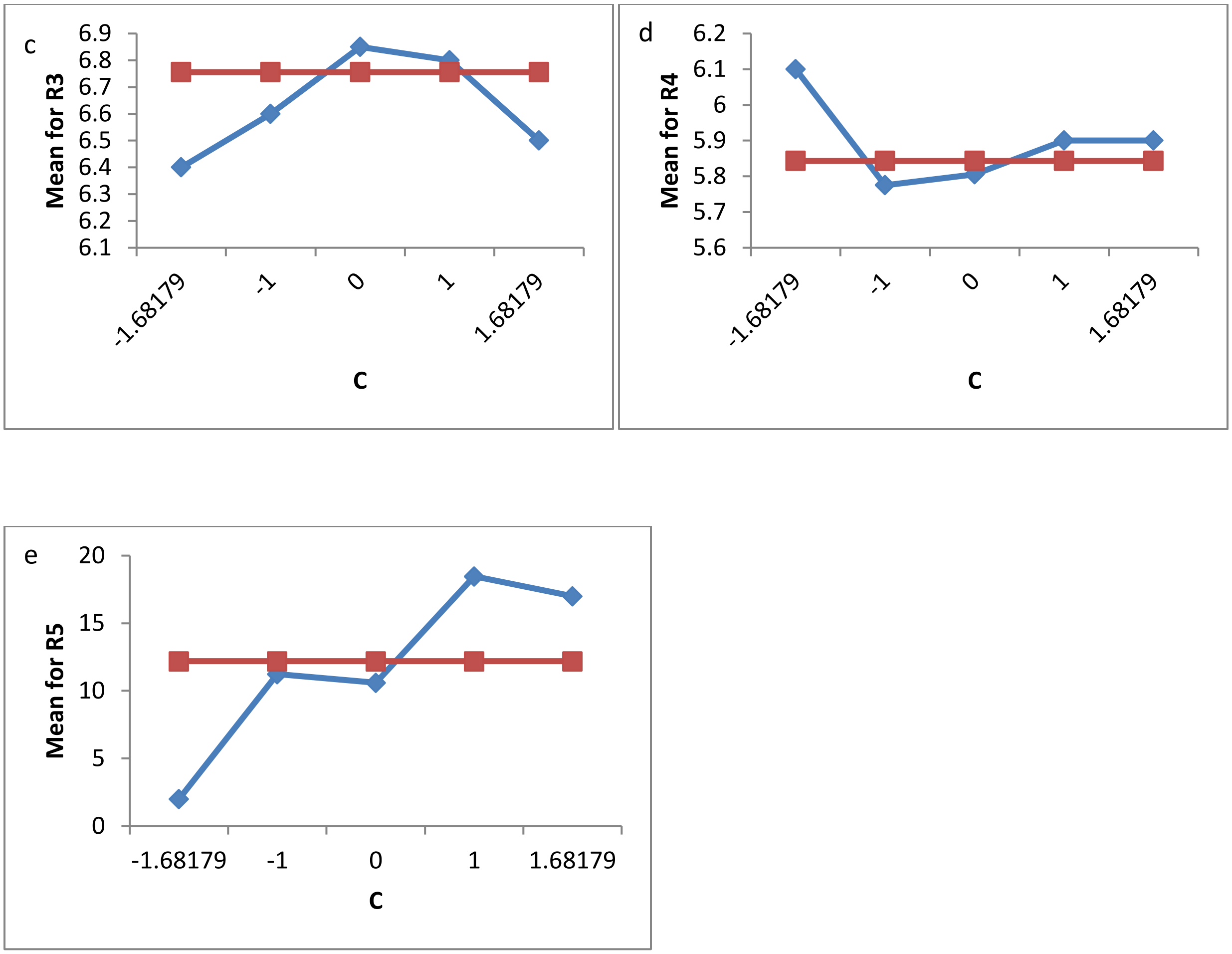


Figure 8: Main effect plot of factor C on all responses

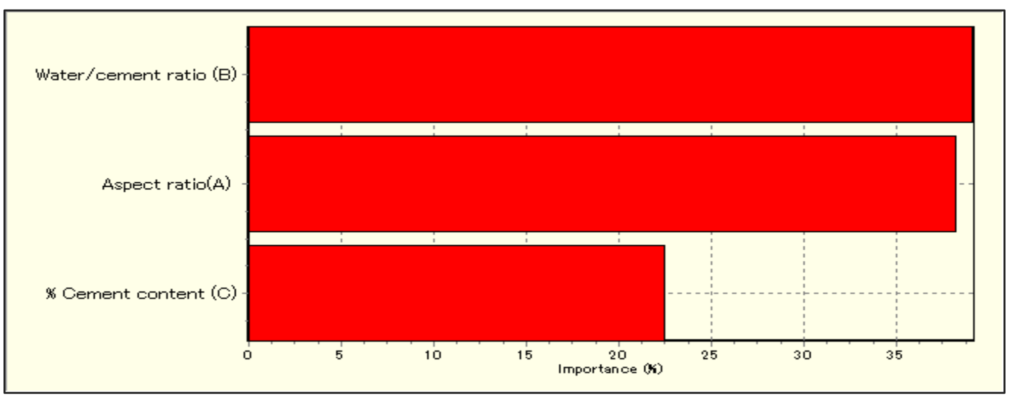


Figure 9: Influence of process variables [33]

### 4.4 Optimization by RSM

The optimization of all response was done using the optimization tool of RSM. The following settings are available for the optimization process; maximize, minimize, in range and target. For the purpose of this study the compressive, flexural split tensile strengths were set at maximum while the water absorption and slump were set at minimum and in range respectively. Under this condition the water absorption, slump

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compressive, flexural and split tensile strengths 0.94 %, 7.65 cm, 42.69 N/mm², 7.97 N/mm²and 5.23 N/mm² respectively. The process variables used to achieve this purpose were 140 for aspect ratio (A), 0.26 for water cement ratio (B) and 40% for cement content (C). The validations of these experimental results are available in our earlier studies [31].

## 5. Conclusion

The study examined the effect of process variables such as aspect ratio, water cement ratio and cement content on the properties of steel fiber reinforced concrete. For better understanding of these process variables two modeling approaches were used namely RSM and ANN. This study found out that although there have been far reaching recommendations in favour of ANN for modeling complex nonlinear relationships of process variables, the RSM model performed better in predicting the investigated properties of steel fiber reinforced concrete measured by the Root mean square error (RMSE), Mean absolute error (MAE), Model predictive errror (MPE) and absolute average deviation (AAD). This may be attributed to the fact that the nature of RSM is structured towards exhibiting the contributions of all coefficients in the regression models which makes it efficient in recognizing the insignificant process variables and their interactions. In addition RSM also identifies insignificant quadratic terms thereby reducing the complexity of the problem and providing better prediction in this study. The in ability of ANN-GA to outperform RSM may be attributed to the fact that five properties of steel fiber reinforced concrete were being predicted simultaneously with ANN-GA training and testing requiring huge search space to provide optimal solutions for a concrete with low water absorption, high compressive, flexural splitting tensile strengths and reasonable slump.

**Author Contributions**: T. F. Awolusi performed the experiments, analyzed and interpreted the data, contributed reagents, materials, analysis tools or data and wrote the paper. O. L. Oke conceived and designed the experiments. O. O. Akinkurolere performed the experiments. O. D. Atoyebi edited the paper. All authors reviewed the manuscript, and approved the final version of the manuscript.

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