



Prediction of A Singly Reinforced Concrete Beam Steel using Artificial Neural Network

S O A Olawale¹, O P Akintunde^{1,2}, M O Afolabi¹ and O A Agbede¹

¹Department of Civil and Environmental Engineering, Bells University of Technology, km 8, Idiroko, Benja Village, P.M.B. 1015, Ota, Nigeria

²Corresponding author: akintt18@gmail.com

Abstract. This paper presents the prediction of a singly reinforced concrete beam using Artificial Neural Networks (ANN). The method was adopted for cost optimization of the structural element and compared with the requirements of Eurocode 2 design. The code provisions for the design of a singly reinforced beam can vary from place to place. The use of a system immune from the code variation is an excellent means of predicting the reinforcement's need of a rectangular concrete beam. In this work, an artificial neural network (ANN) is employed to forecast the reinforcement of such a beam. Artificial neural network has the potential to simulate the data that are hard to produce in arithmetical analysis. The scheme was established using the MATLAB tool kit. The design variables were the depth of the beam, the width of the beam, and the moments. A forward pass supervised backward propagation training. The regression analysis of the results is one to one match. The predicted and target values are completely in accord.

Key words: Artificial neural network (ANN), regression, forward pass, backward propagation, Eurocode 2 (EC2), MATLAB.

1. Introduction

In many countries, concrete is the main construction materials and the structural design of the structural elements is code-based. There is variation across the board from country to country without a unified approach. The British (BS8110) and the European Union (EC2) codes are similar in outlay and considerations [1,2]. However, the American code (ACI) is a complete digression but with reasonable similar outputs [3]. It is reasonably difficult to harness all the codes available today to be a single universal source of design provisions. The British and EC codes are almost the same with slight variations of some prescribed constants. Artificial neural network provides a means of a quick prediction of the required reinforcement once trained successfully. The first work on human brain activity patterns was published by William James in 1890 [8]. The brain constitution of neurons and synapses are the basis for the development of an artificial neural network. ANN is modeled on the principle of brain workings. This has proven to be of immense contribution to modeling complex and difficult systems to a very good accuracy. Warren McCulloch and Walter Pitts (1943) [9],

attempted to demonstrate how the brain can work using electrical circuitry whereby a summation over-weighted inputs and the activated output using this input. By 1951, Marvin Minsky [10], developed the first ANN. This is an abstraction of the human brain functionality. The human brain is made up of interconnected neurons sending signals through the synapses to one another. This is the model captured in the ANN whereby the weighted biased inputs are aggregated into the each neuron

with activation functions to transfer the outputs to the next layer of neurons until the output layer neurons compute the final outputs.

ANN can be a single layer or multi-layer network that can be supervised or unsupervised trained. The supervised training is more suited to a predictive neural network. The training algorithm is weight adjustment on backpropagation. The weight adjustment value calculation is based on gradient descent whereby training rate value and the descent direction are optimized. The inputs into the ANN can be one or many depending on the problem at hand. The outputs also can be one or many as well. Most of the structural predictive neural networks are two or three-layer networks depending on the nomenclature of definition. The input layer is often not seen as part of the layers in the network. Many researchers have applied ANN to solve structural engineering problems relating to either strength, flexural or design predictions. [1] applied ANN to predict the flexural design of concrete hydraulic structures and they established a good agreement between calculated and predicted values. [2] Successfully applied ANN to assess the load-carrying capacity of reinforced concrete members. They found an excellent agreement between the calculated and predicted results. [3] Applied ANN to design some reinforced concrete members. Despite their limited amount of data to train their network, the agreement between their AN predicted values and calculated ones is reasonable. Works on the prediction of compressive strength, shear capacity, and tensile strength of the reinforced concrete beams have been explored to a greater extent. One such is the work of Vingnesh Shanoy B, Alisha B B, Karthik, Shraddha P, and Skanda P (2016) whereby the compressive strength of concrete was predicted using ANN [4].

In the present study, the appropriateness of ANN to predicting the reinforcement of a concrete loaded to less than the ultimate moment carrying capacity is investigated. The sensitivity of the number of neurons in the hidden layer is investigated to determine the most efficient network topology without overtraining.

2. Materials and Methods

The materials required to prospect the present work are excel and MATLAB software. The provisions of EC2 are implemented into the excel spreadsheet calculations to generate training data for the network. Two-layer networks with three inputs (width, depth, and moment), one hidden layer of number of neurons to be determined through parametric investigation and one output, the steel ratio. The topology used is shown in figure 1 and the computational model for the forward propagation is shown in figure 2. The activation function used is simoid function and the training algorithm used is Levenberg-Marquardt. The training data was generated using excel whereby the EC2 design provisions were implemented. The three variables considered are width, depth, and moment. The plots of the training data are presented in figures 3 to 5. The training data is partitioned into 70, 15, and 15 percentages for training, validation, and testing respectively. The MATLAB ANN tool kit is used to implement the scheme. The choice of the network in terms of the number of neurons in the hidden layer is based on the distribution of the error on the zero error and the performance value of the network. The number of neurons with less skewness of the error histogram and with the best performance value will be selected to be the representative network.

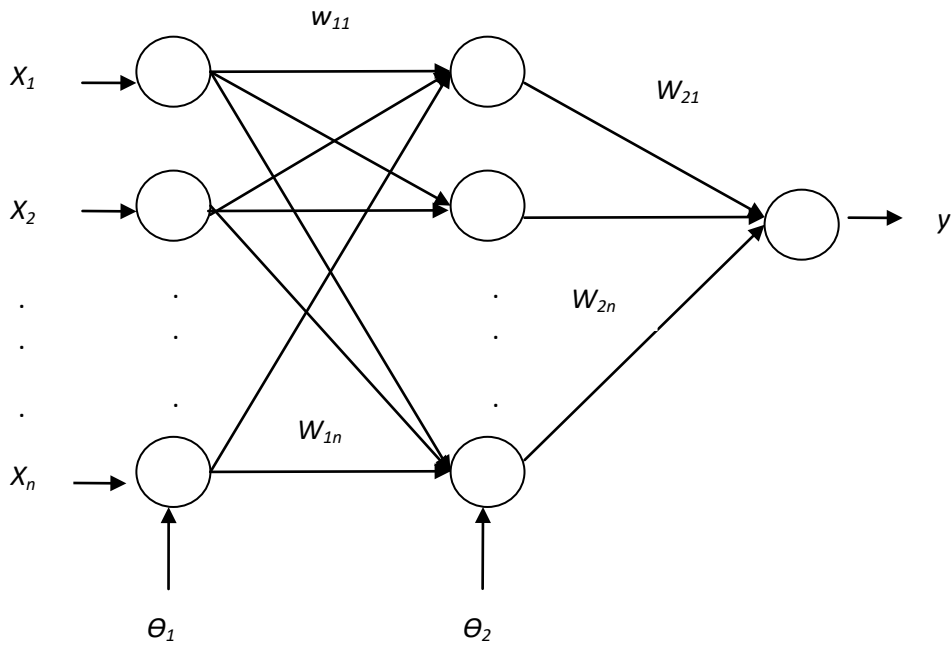


Figure 1. Neural Network Topology adopted

The number of input is 3 and the numbers of neurons in the hidden layer are between 5 and 15 neurons.

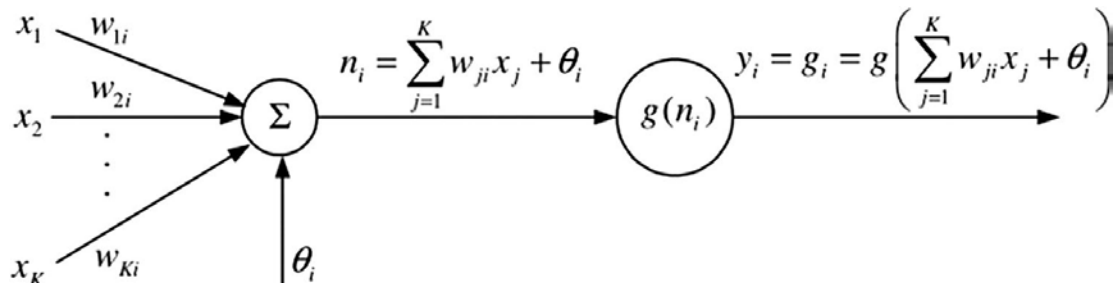


Figure 2. Typical computation scheme for the ANN (forward pass)

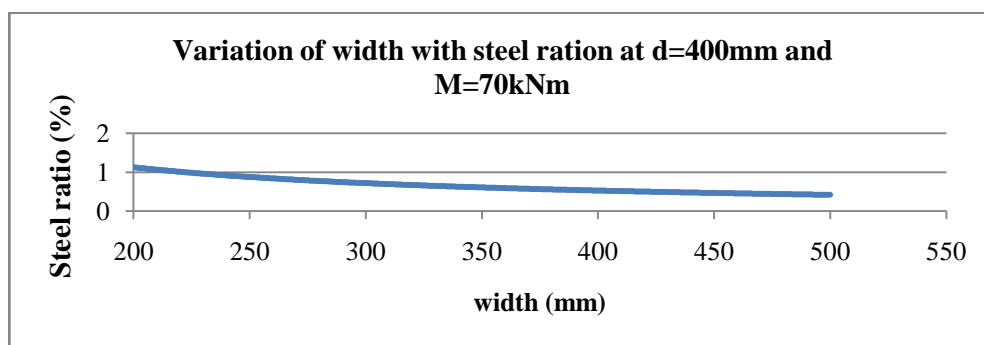


Figure 3. Width to steel ratio variation

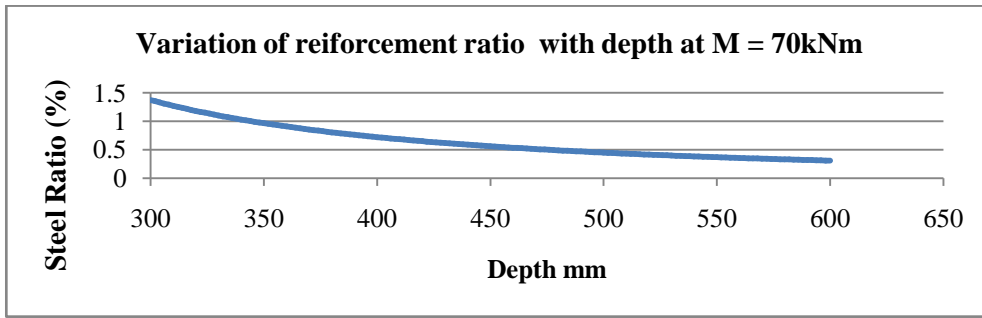


Figure 4. Depth to steel ratio variation

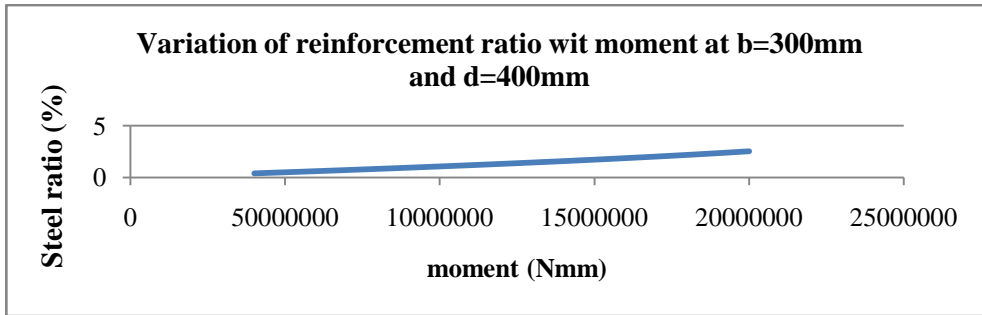


Figure 5. Moment to steel ratio variation

3. Results and Discussion

The results of initial experimentation to determine the number of neurons in the hidden layer are presented in Figures 6 to 8. The error histogram for ten neurons exhibits the least skewness around the zero error. This means that ten neuron hidden layer is chosen.

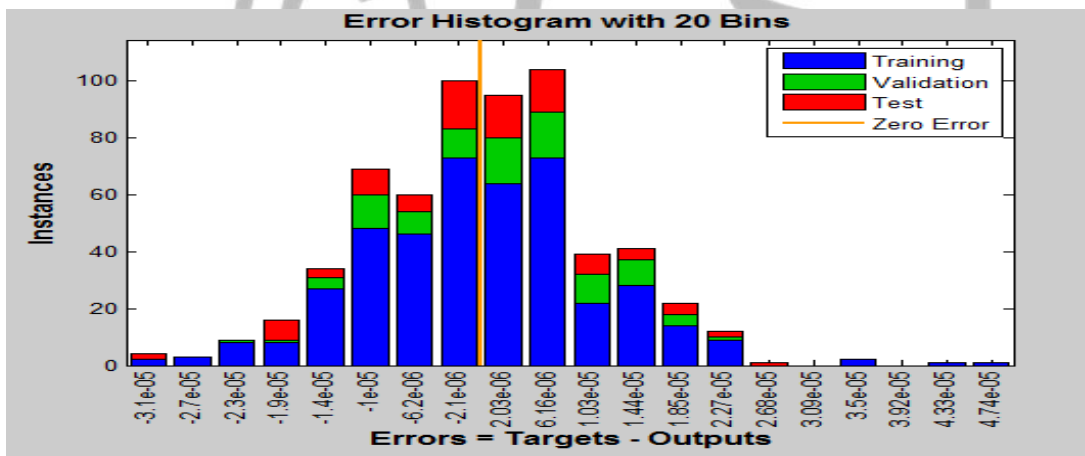


Figure 6. Five neurons in hidden layer error distribution around zero error

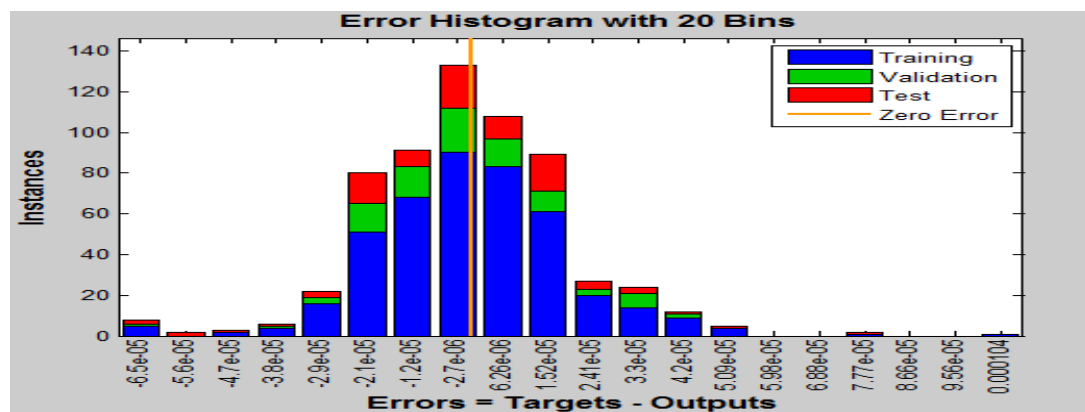


Figure 7. Ten neurons in hidden layer error distribution around zero error

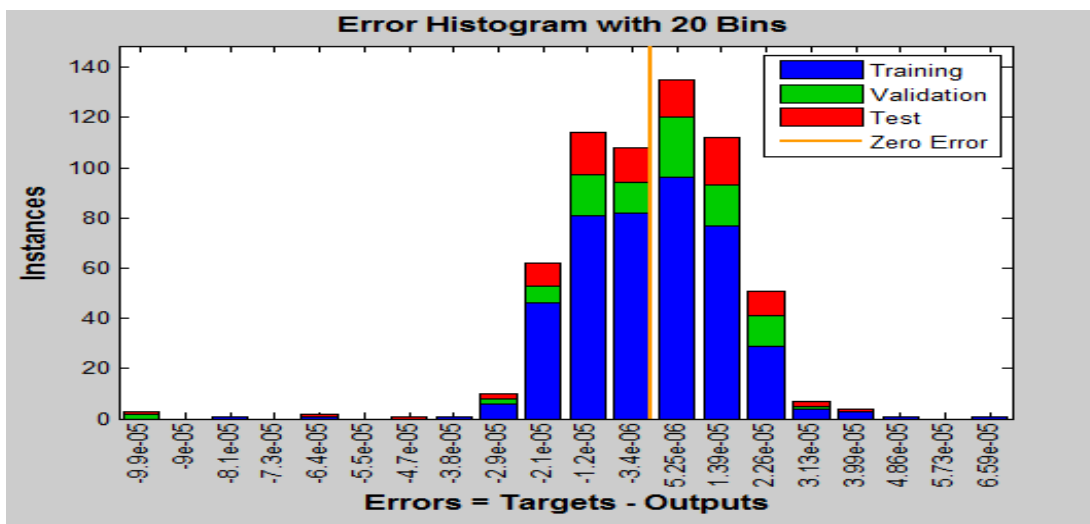


Figure 8. Fifteen neurons in hidden layer error distribution around zero error

Figure 9 shows the final adopted network implemented to predict the steel requirement for concrete loaded below its maximum load-carrying capacity. The front page of the MATLAB ANN tool is shown in figure 10 and the performances of the training, validation, and testing are shown in Figure 11.

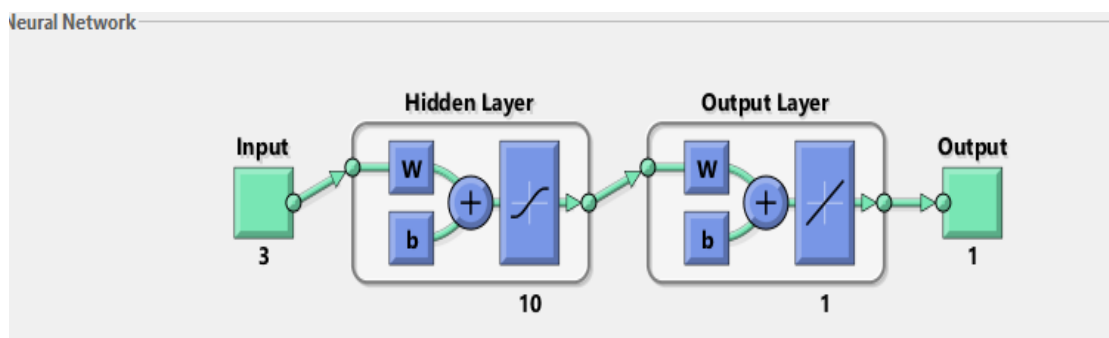


Figure 9. Neural Network used in the prediction of the reinforcement

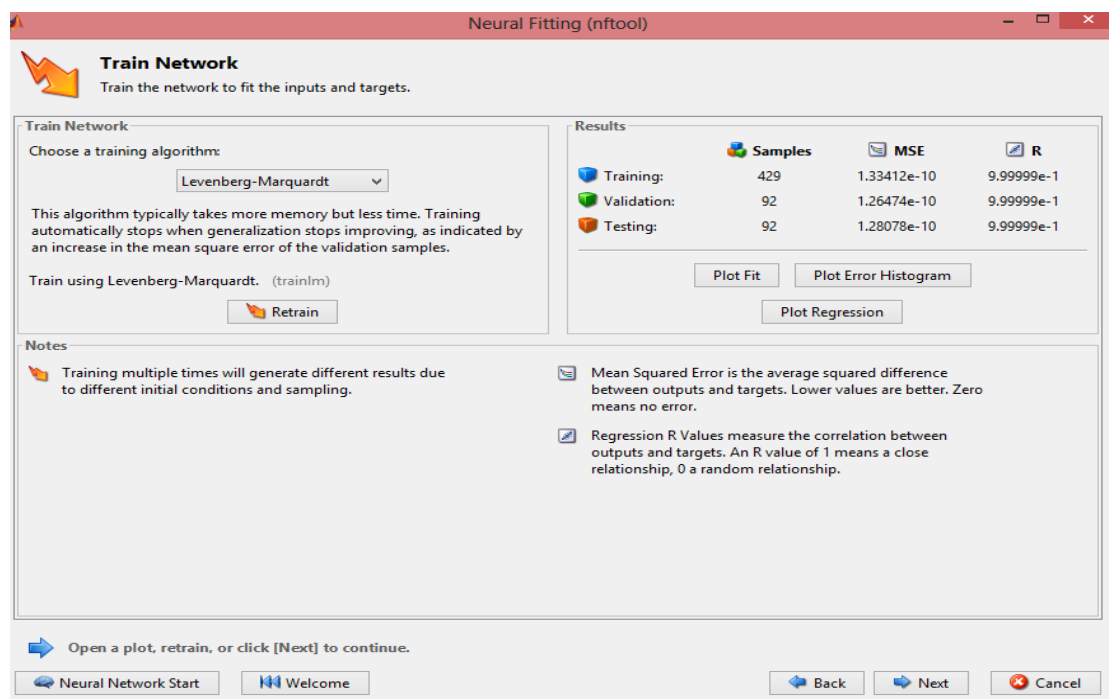


Figure 10. ANN Tool page showing the information on the Error and Activation function

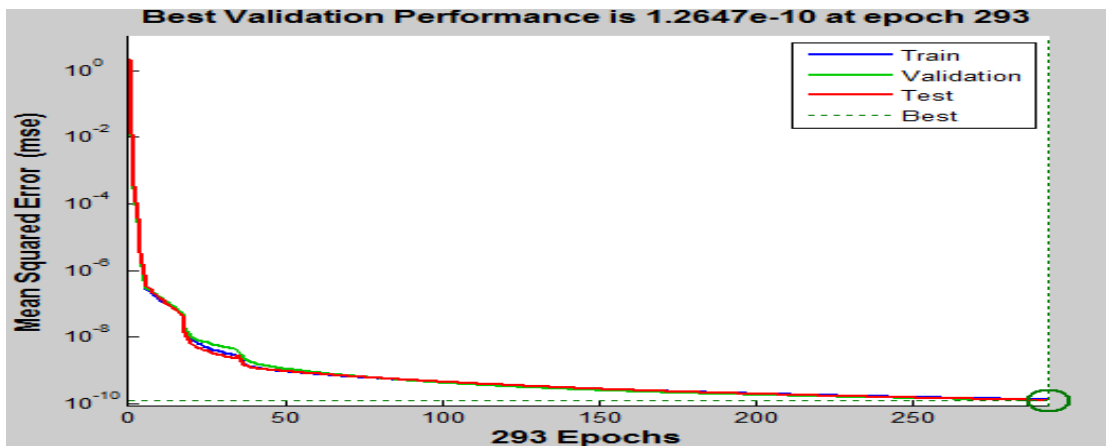


Figure 11. Performance evaluation of the training, validation and testing

The regressed predicted results against the calculated results in Figure 12 for the training, validation, testing, and all. The excellent agreement between the computed and the predicted results are outstanding.

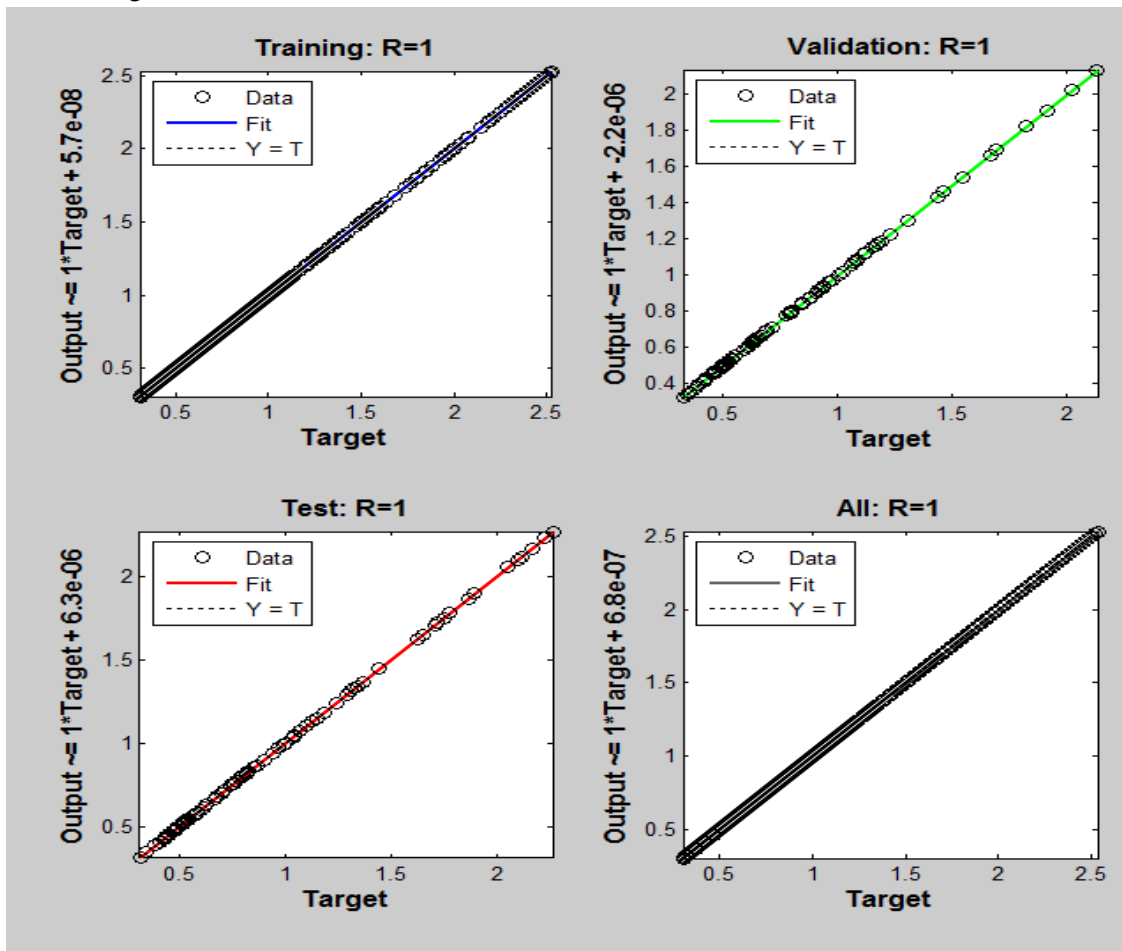


Figure 12. The regression of plots of training, validation, testing and all

4. Conclusion

From the results of the previous section, it is obvious that the agreement between the computed and predicted results is excellent. It has been established that ANN can be used to design a singly reinforced rectangular beam without reference to any code of practice. The requirements of the codes are satisfied with the optimum result obtainable. This leads to the cost minimization of the reinforced concrete beam. Artificial Neural Network is beneficial in terms of producing original outputs from the

training of given samples through accurate prediction of results thereby analyse information very rapidly and adjust to modifications in the initial problems.

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