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DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODEL IN PREDICTING PERFORMANCE OF THE SMART WIND TURBINE BLADE

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ABSTRACT

This paper demonstrates the applicability of Artificial Neural Networks (ANNs) that use Multiple Back-Propagation networks (MBP) and Non-linear Autoregressive with Exogenous (NARX) for predicting the deflection of the smart wind turbine blade specimen. A neural network model has been developed to perform the deflection with respect to a number of wires required as the output parameter. The parameter includes load, current, time taken and deflection as input parameters. The network has been trained with experimental data obtained from experimental work. The various stages involved in the development of genetic algorithm based neural network model are addressed at length in this paper.

Keywords: Artificial neural network; back-propagation; multiple back-propagation; non-linear autoregressive with exogenous.

INTRODUCTION

Glass fibre reinforced polymer (GFRP) is a promising material for renewable energy which has been mainly used in the wind turbine blade. The choice is due to high and strength weight ratio (Nolet 2011). The application of GFRP laminates improves the ultimate strength in capturing wind as proportional diameter of the blade (Sorensen et al. 2004). However, a longer blade will result in deflection since the bending moment is high from the tip to root. At this point there is more blade outboard (contributing to bending moment) than at any other point along the blade (Peter & Richard 2012). At the tip the bending moment drops to zero as shown in Figure 1. The nature of the composite material is a high non-linear system. It is very crucial problem to describe the characteristics of composite load deflection. To alleviate the deflection of the GFRP, it will be enhanced to use Shape Memory Alloy (SMA) wires (Supeni et al. 2012a; Supeni et al. 2012b). As the Artificial Neutral Network (ANN) has a strong ability of describing non-linear mapping, there are many uses in load modelling studies, and researchers have been trying to describe the complex characteristics of the performance of the composite load precisely (Sapuan & Iqbal 2010). The neural network is used in the parameter identification of traditional such as difference equations model, power function model and polynomial function model, but the BP neural network is only used as an optimization algorithm, and the structure of the models have not improved; disadvantage such as slow convergence and local minimum (Gayan et al. 2013). The performance of GFRP plated specimens depends on the load applied, internal structure of SMA and current applied. This paper presents the results of experimental investigations carried out on 6 SMA wires reinforcing a rectangular plate along with an Artificial Neural Network (ANN) based model for performance prediction.

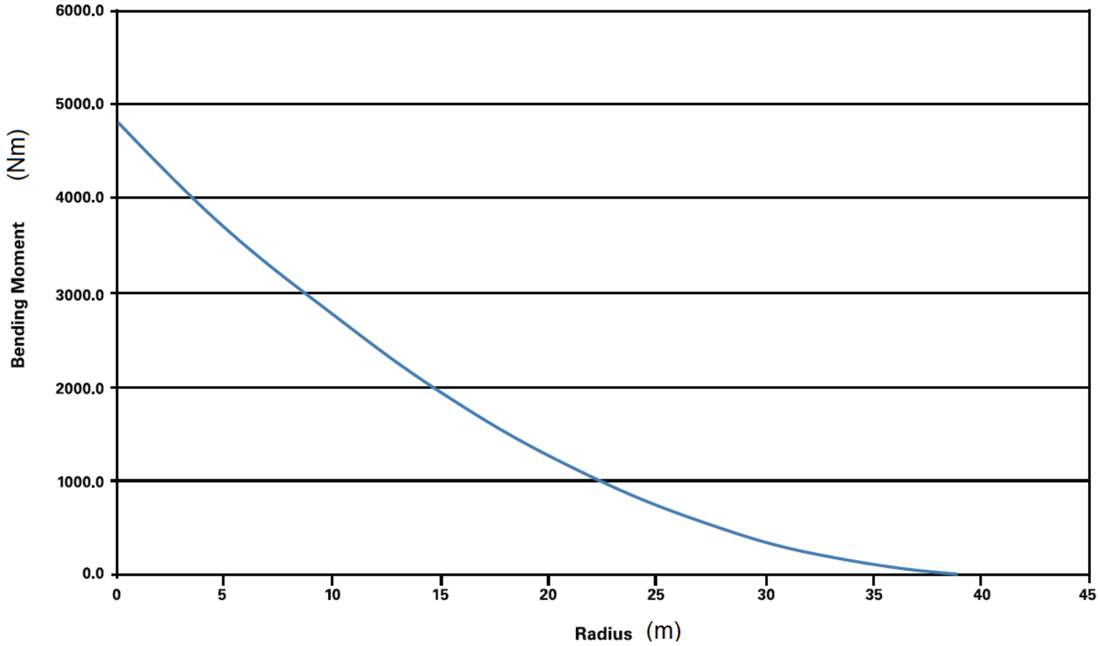

Figure 1. Bending moment against radius in a large turbine blade (Nolet 2011).

RESEARCH SIGNIFICANCE

The effect of current applied of SMA wires and correlation of the deflection of the plate has been modelled in ABAQUS in Figure 2 and tested experimentally in Figure 3 (ABAQUS 2012). The results obtained from the investigation were used to generate an ANN based design tool for predicting the amount of wire needed to restore the original shape of such bending. This depends on parameters such as deflection, the total current and the applied load.

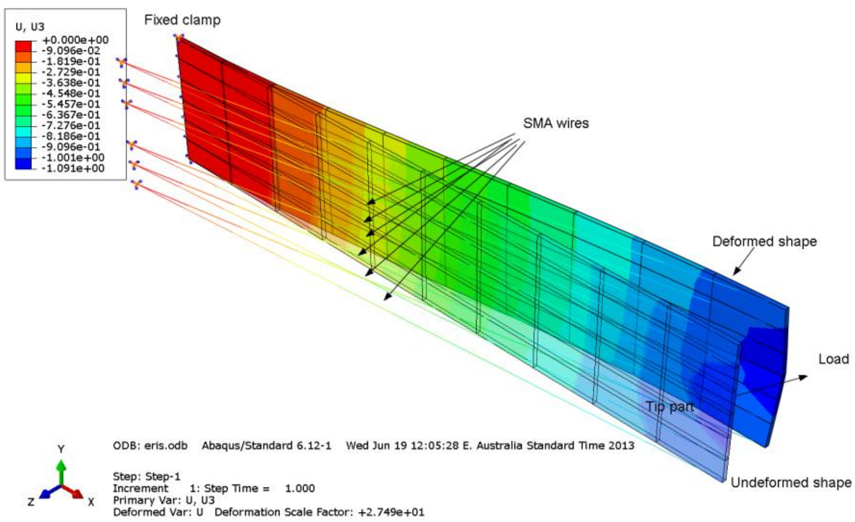

Figure 2. The plate simulated in ABAQUS FEA.

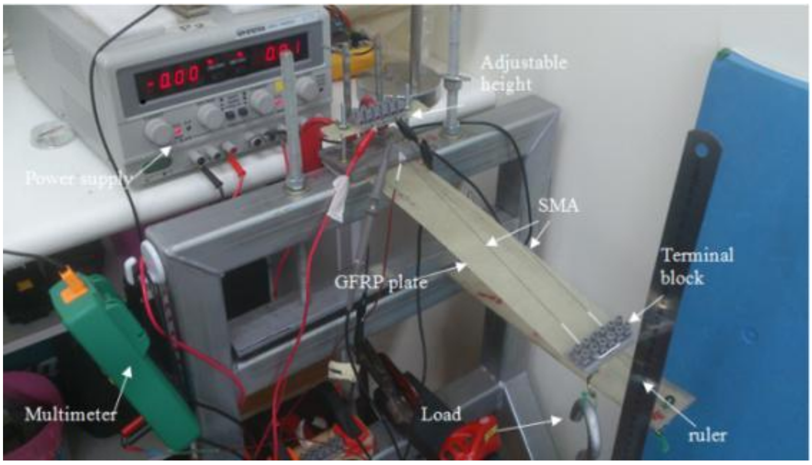

Figure 3.Photograph of tested composite plate.

METHODOLOGY

This study is to evaluate the predictive ability using Machine Learning (ML) which is MBP and NARX. The performance comparison between Multiple Back-Propagation (MBP) and Non-linear Autoregressive with Exogenous (NARX) are undertaken. To facilitate the performance comparison, all networks simulated have been designed and trained accordingly from output layers, hidden layers and output layers. Output neurons use hyperbolic tangent activation functions. The standard back-propagation algorithm is used to train the networks with learning rate equal to 0.01. Once a given network has been trained, it is required to provide estimates of the future sample values of a given time series for a certain prediction. The predictions are executed in a recursive curve until desired prediction horizon is reached, i.e., during N time steps the predicted values are fed back in order to take part in the composition of the regressors. The networks are evaluated in terms of the root mean square error (RMSE). The parameter such as applied load (L), applied current (I) and deflection (d) have been used as input and number of wire (NW) as the output to designed ANN. The general schematic diagram is illustrated in Figure 4.

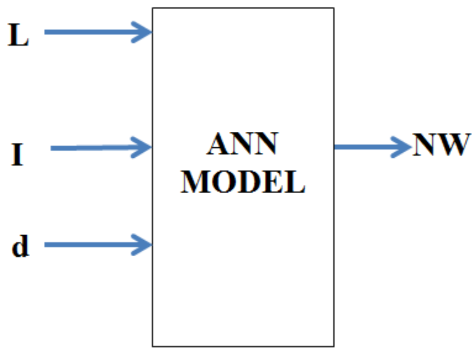

Figure 4. General structure of model ANN.

The network structure of the proposed ANN was divided into three randomly selected batches. The batches comprised of the training batch, testing batch and validation batch. The regression analysis capacity of the network could be checked after training phase. The mean square error (MSE), determination coefficient R and root mean square errors (RMSE) were measured by the suggested neural network. In total, 162 data sets were selected for the design of ANN which were broken down into each target time steps which were 130, 16 and 16 for training, testing and validation respectively.

MBP Method

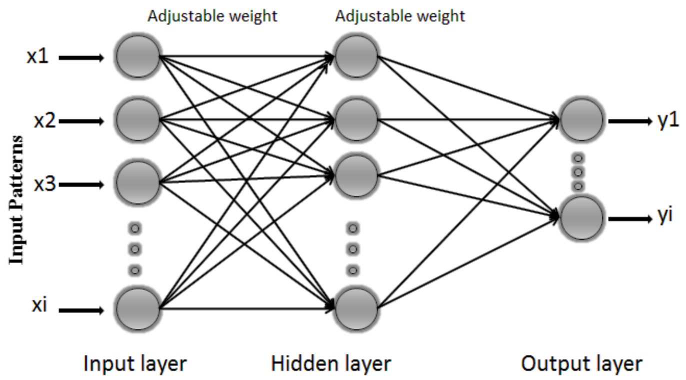

Figure 5. Diagram of MBP network.

Figure 5 illustrates a learning process of multi-layer neural network employing back propagation algorithm. To illustrate this process the three layers neural network, for example, three inputs, three hidden layers and one output were implemented. Two types of sigmoid activation functions were selected for several numbers of hidden, output layer 2 which are logarithmic sigmoid function (logsig) and hyperbolic tangent sigmoid function (tansig) respectively. The adjustable weights used to propagate errors back were equal to the one used during computing output value. Only the direction of data flow was changed (signals are propagated from output to inputs one after the other). This technique was used for all network layers. For comparative study, a free opened source software has been used to generate the MBP which use program code C (Noel & Bernardete 2001; Noel & Bernardete 2003) .

NARX Method

NARX which is depicted in Figure 6, has been used to predict values of a time series, y(t), from past values of that time series and past values of a second time series, x(t). In this experiment, NARX consists of numbers of hidden layers, numbers of delay lines (D) and one output neuron with two layer feed forward networks were used in these experiments. The standard Lavenberg-Marquardt (LM) back propagation algorithm is used to train the network with learning rate close to 0.001. The method of regularization has been used which consist of 1000 epoch and the regularization parameter used is 1.00e-05. MATLAB code has been used to run the ANN toolbox (nntool) that has been generated by using the mode LM back-propagation (trainlm)(Howard & Mark 2000).

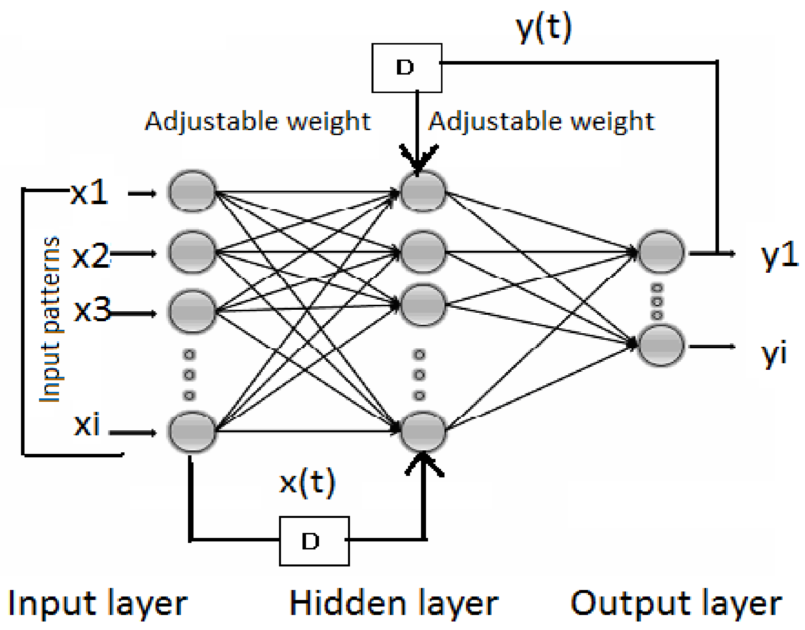

Figure 6. Diagram of NARX network.

RESULTS AND DISCUSSION

The number of SMA wires applied has been considered as an output vector. Applied current, deflection and load are considered as the input vectors. All calculations of neural network were made using MATLAB (Levenberg-Marquardt) and MBP open source code. The schematic diagrams of the both models are displayed in Figure 7 and 8. Both LM and MBP algorithms for training were applied to the network. The application randomly divides input vectors and target vectors into three sets, as follows. 80% are used for training. 10% are used to validate that the network is generalising and to stop training before over-fitting. The last 10% are used as a completely independent test of network generalisation. Data from experiments were collected to train the performance deflection number of wire with response to the load applied, deflection and the current applied. About 162 values of data were used for these networks. Table 1 shows NARX1 model with the lowest MSE among other model of ANNs and the fastest mode convergence training network. As can be seen from Table 2, the smallest values of MSE and the high values of R give us reason to consider the obtained NARX models as adequate which are almost to unity.

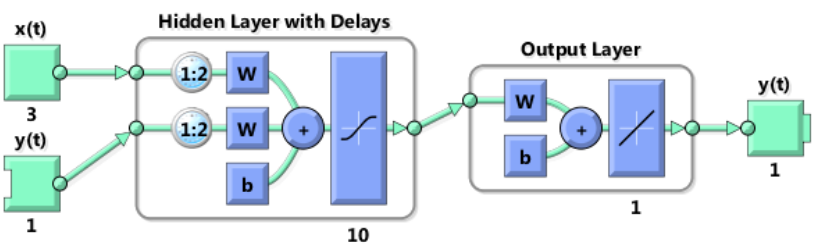

Figure 7. Example of NARX network with 10 hidden layers and 2 delays time by MATLAB.

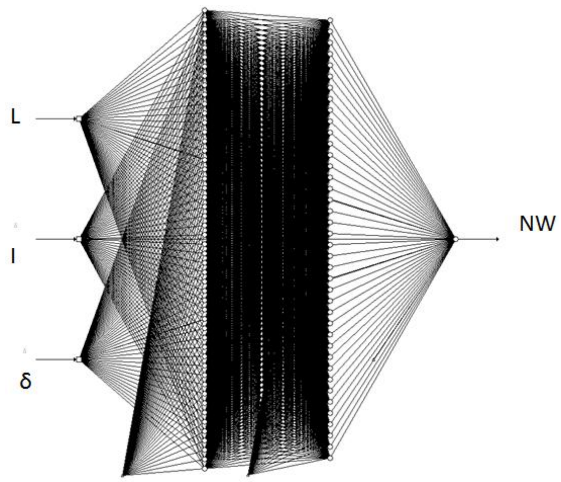

Figure 8. Example of MBP diagram network with 50-40 hidden layers.

Table 1.Predicting the deflection with respect to number of wires using various model.

Model	**Input vector**	**Output vector**	**Structure/No hidden layer neuron**	**Epoch (No. of Iteration)**	**Mean Square Error (MSE)**
MBP1	L,I,d	NW	50-40	1,273,277	0.009999
MBP2	L,I,d	NW	50-40-30-20	437,788	0.009997
NARX1	L,I,d	NW	10 delay time 2	26	0.000308
NARX2	L,I,d	NW	10 delay time 3	10	0.001542
NARX3	L,I,d	NW	10 delay time 4	7	0.002337

Table 2. The detail results of the NARX model training for NARX.

	Target value	**MSE**	**R**
Training	130	8.12988E-5	9.99145e-1
Validation	16	3.08830E-4	9.99289e-1
Testing	16	3.49000E-3	9.99597e-1

The best validation performance is provided in Figure 9. It shows that the process of the network's performance has improved during training. This performance is measured in terms of MSE and it is shown in log scale. It is evident that the MSE has decreased rapidly along epochs while the network is trained. In this case, the results are reasonable considering the final mean-square error is very small which are the test set error and the validations set error that have similar characteristics. In Figure 10, the training, test and validation data indicate good curve fitness. The validation and test results also show that the overall values is greater than 0.9. Figure 11 shows how the error sizes are slightly well distributed. Typically, when most errors are near zero, it has been observed a better trained model. In this case however, it is confirmed that the network also have errors near zero.

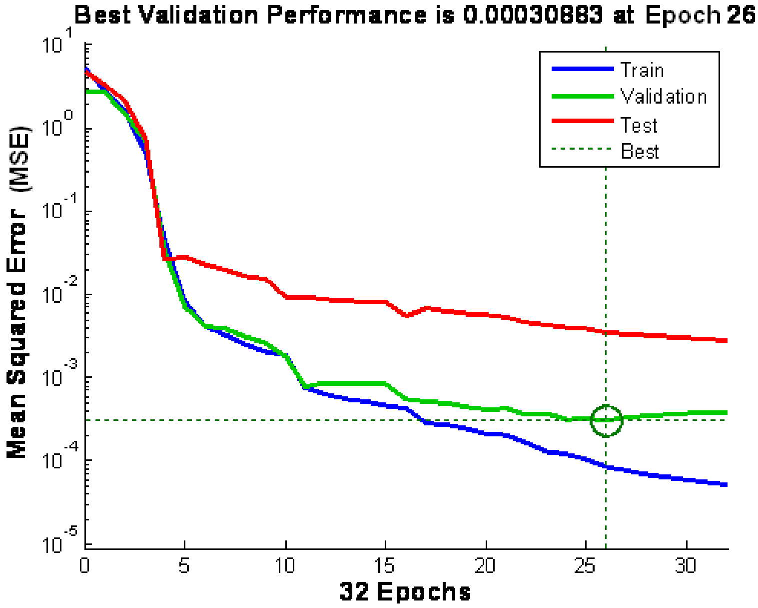

Figure 9. The network's performance.

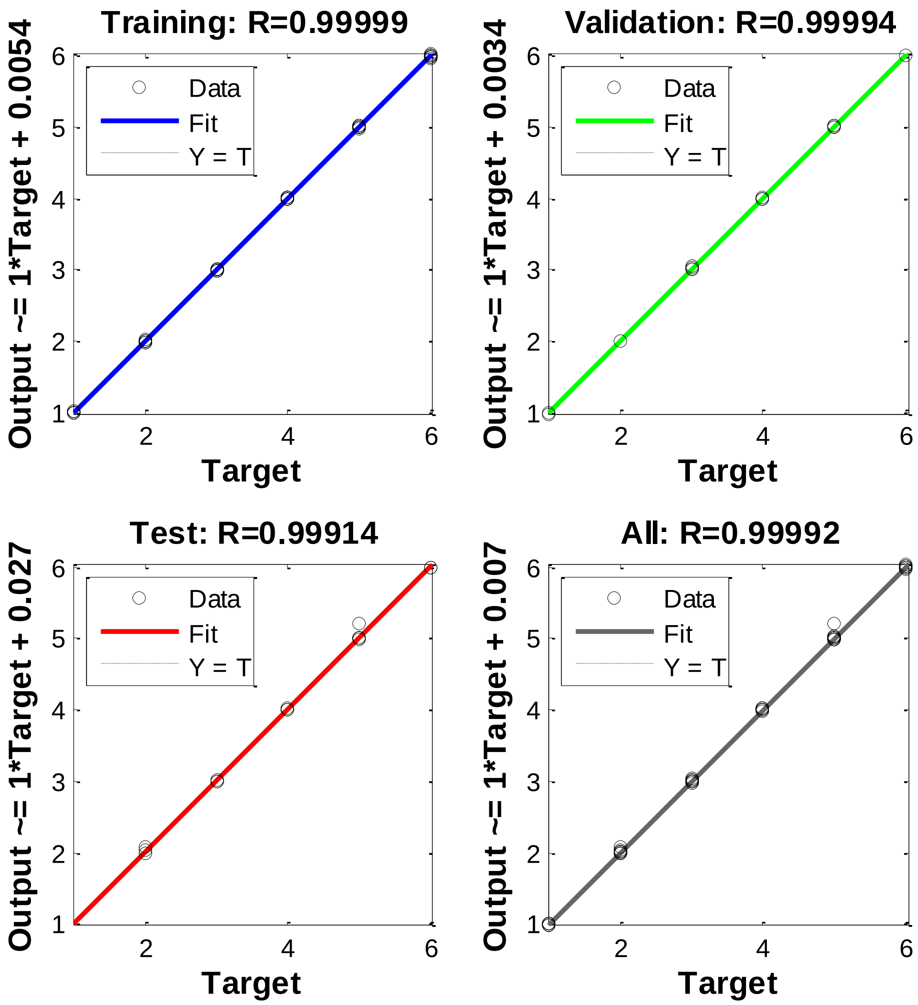

Figure 10. Regression analysis plot for the NARX .

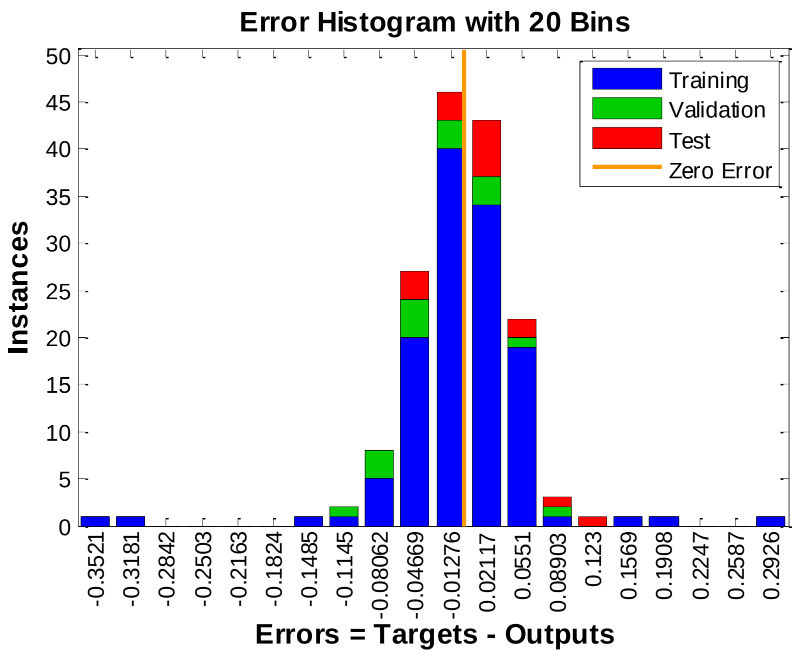

Figure 11. Error histogram of the NARX prediction model

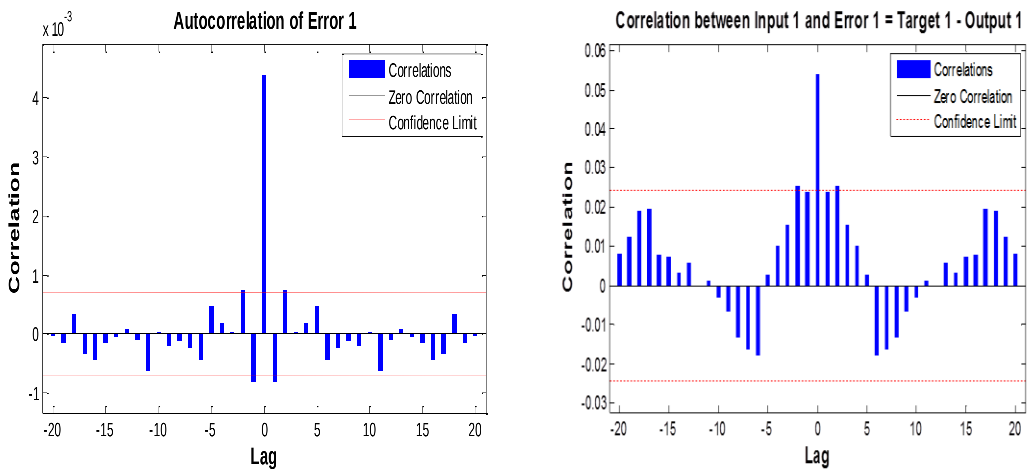

Figure 12. Auto-correlation of errors of NARX prediction model and correlation between input and output with respect to target function.

The correlation between input and error is provided in Figure 12. This figure illustrates how the errors are correlated with the input sequence. The perfect prediction model means that all the correlations should be zero. In this case, all of the correlations are within the confidence bounds around zero. The function of auto-correlations of errors is used to validate the network performance. Auto-correlation describes how the prediction errors are related in time. For the perfect model, there should be only one non-zero value of the auto-correlation at zero lag. This means that there is no correlation in prediction errors with each other. In this case, the correlations, except the one at zero lag, are within the 95% confidence limits. Based on the various diagnostics described up to now, it can be concluded that the model is adequate. Figure 13 confirms that the responses, obtained from the NARX prediction model for the performance deflection, are adequate, since the errors are quite small. For comparison, similar shape also has been obtained as shown in Figure 14. The predictions obtained based on both methods of network training, the NARX has improved the training network compared to the MBP networks. In MBP, there are still network output errors with respect to desired output network. Although the errors are not correlated with the input sequence, all the correlations are not within the 95% confidence limit.

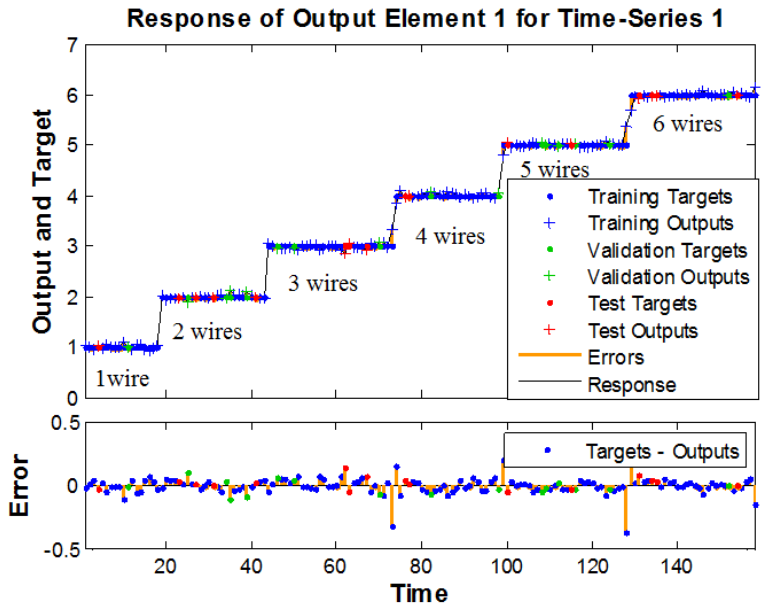

Figure 13.Response of NARX prediction model for performance deflection (trained by the Levenberg- Marquardt algorithm)

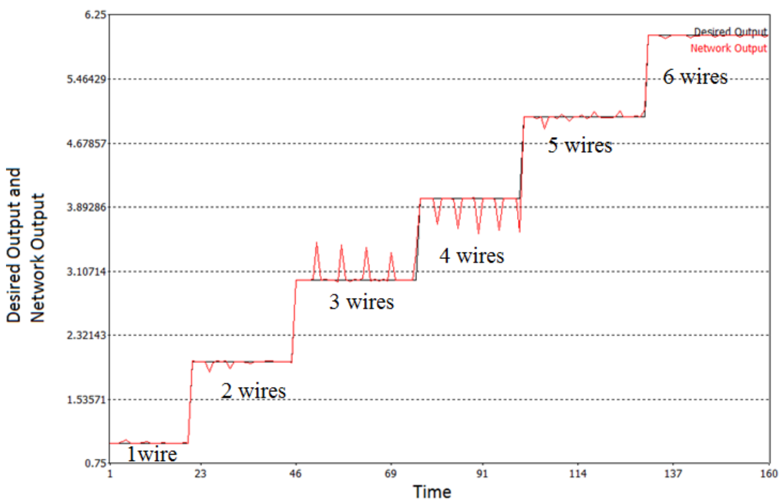

Figure 14. The desired output and network output by MBP by opened source C code

CONCLUDING REMARKS

In this study, the ANN model with different network training methods was applied for predicting the amount of wire needed to restore the original shape that recover from deflection. The NARX and MBP algorithm for training of the network were used. The first conclusion of the paper is that although neural models may frequently suffer from a certain degree of inaccuracy, the results show that the NARX model applied to the deflection of SMA has proven the productivity and relation quality, while using less of computational expenses. The NARX model was chosen since it resulted in the best performance, according to MSE. Therefore, the NARX models have the potential to capture the dynamics of non-linear systems. The second conclusion is that the NARX models are mainly dependent on the applied architecture and training method. Within the context of architecture, the behaviour of NARX models mostly depends on the numbers of neurons in hidden layers. Too many hidden neurons in network cause over-fitting that, in turn, leads to poor predictions. Future modeling of the NARX is to model ANN 2 and ANN 3 which use deflection and applied current as the output vectors respectively.

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