

# Integration of Artificial Neural Network and Expert System for Material Classification of Natural Fibre Reinforced Polymer Composites

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**Abstract:** Diversified choice of materials from natural fibre reinforced polymer composites with similar properties complicate the materials selection for engineering products. Implementation of expert system alone makes it difficult to scrutinize the vast selected materials. Hybrid of expert system with neural network technology is desired. Classification of material through neural network under various criteria influences the decision in narrowing down the selection. In this study, the integration of artificial neural network with expert system for material classification is explored. The computational tool Matlab is proposed for classification and the materials focused were natural fibre composites. Levenberg-Marquardt training algorithm, which provides faster rate of convergence, is applied for training the feed forward network. The system proves to be consistent with 93.3% classification accuracy with 15 neurons in the hidden layer. The validation of the output is compared with the target on the basis of desired mechanical properties of natural fibre reinforced polymer composites for automotive interior components.

**Keywords:** Artificial Neural Network, Expert System, Material Classification, Natural Fibre Composites, Feed Forward Network

## Introduction

The innovation in material science and technology reveals more materials than ever before and the selection menu become countless for the engineers. Ashby (2004) described the available materials for the engineers are vast and expected to something over 120,000 materials of choice. Materials selection is an important criterion for engineering applications. The explosion all over the world is increasingly using the computing power to solve a complex engineering problem that offers optimum solution. Artificial Neural Network (ANN) was a powerful computational model that simulates the neurons of a biological nervous system. It consists of a set of connected cells called neurons. The neurons receive impulses as input and perform transformation of input information and transmit to output neurons (Yegnanarayana, 2009). It deals with non-linear problems for an accurate

analytical solution. It can learn to detect complex patterns in data by training and thus classifying it while testing with real data. ANN provides practical solution for pattern recognition, classification and optimization problems. It is also used in signal processing, speech recognition, condition monitoring and functional approximation.

Somkuwar *et al.* (2011) used expert network with integration of radial basis neural network architecture for materials selection. Sensorial properties and cost of steel metal were considered for selection. They developed the expert system with visual c++ and integrated with neural network tool box of Matlab. Sapuan and Mujtaba (2010) developed a neural network based materials selection system for selecting optimal material from natural fibre polymer composites. They implemented back propagation algorithm to correlate between the inputs and to predict the output materials. Further the predicted output was processed using multi-attribute ranking

method to select most suitable material. Golmohammadi (2011) described a model for decision making by implementing artificial neural network for fuzzy multi-criteria decision making problems. The technique of pairwise comparison from analytical hierarchy process was applied to rank the criterion and feed forward method was used to train the network. The model was demonstrated in detail for suppliers' performance in product evaluation. Goel and Chen (1996) demonstrated the application of neuro-expert network for materials selection. They utilized neural network connectionist approach with back propagation for training data samples. The expert system evaluated the output of neural network on the basis of price, availability in stock and closeness to desired material properties. Fazilat *et al.* (2012) proposed a new method for predicting the mechanical properties by Artificial Neural Networks (ANNs) and adaptive Neuro-Fuzzy Inference System (ANFIS) in polymer composites. They made brief instruction to the theoretical background and constructed ANNs and ANFIS models and employed them for analyzing the results with 16 data sets. They claimed that the obtained results were well adopted with minimum errors.

Smith *et al.* (2002) found that neural network approach was suitable for powder metallurgy modelling for materials selection purposes. Multiple inputs, modelling of highly non-linear responses and the avoidance of noise effects had been provided by training a back propagation neural network with experimental data. The neural network deductions for process inputs were compared to those generated by regression analysis. Charniya and Dudul (2011) developed a prototype for classification of material type and surface roughness. An optimum Multilayer Perceptron Neural Network (MLPNN) model was designed using digital signal processing tools to measure the bouncing plunger probe on the plain surface. The signal generated from optical mouse was recorded on a PC and a three layer neural network classifier with 19 neurons in the hidden layer-1 and 20 neurons in the hidden layer-2 was found to be optimal for training the network with conjugate-gradient learning algorithm. Thus neural network classifier consistently performed with 97.5% accuracy for non-linear classification.

Zhou *et al.* (2009) presented their approach for multi-objective materials selection in sustainable products. They implemented artificial neural network with genetic algorithm for optimizing the multi-objectives of materials and selecting the best candidate materials. They took into consideration not only the mechanical and economical properties (Sapuan and Abdalla, 1998), but also the environmental factors for selection. However, to the knowledge of the authors, limited studies have been conducted on materials selection of natural fibre reinforced polymer composites with ANN.

Natural Fibre Composite (NFC) is an emerging alternative material for petro-chemical material to

enforce the green technology (Ahmed Ali *et al.*, 2013) and this sustainable material is the dire need of this globe to protect environmental consciousness. It has a potential market segment and significantly penetrates all the applications and mainly in automotive industry (Mohanty *et al.*, 2005). The percentage of natural fibre reinforced composite in the market segment is shown in Fig 1. The properties of NFC significantly change depending on the climate and environmental conditions and it was hard to predict the values as it goes with different fibre loadings (Sapuan *et al.*, 2003). Therefore prediction of output using ANN alone would not produce a worthy result.

The above literature review inspires the incorporation of rule based expert system with ANN technology for material classification. In this study we focus on few properties of natural fibre composite used as an alternative material for synthetic materials in the interior component of automobile. The objective of this research is to integrate the ANN with the expert system output to classify the natural fibre composite materials in accordance with the range specified in product design specification.

## Methodology

The proposed system in this research comprises an expert system integrated with a neural network for material classification. The present research is an elaboration of the authors' previous research work on rule based expert system which was applied for optimum selection of natural fibre composite materials (Ahmed Ali *et al.*, 2013). This materials selection procedure accommodates two steps of approach with three modules; the first by implementing the Java based expert system through the programming tool NetBean, to identify those candidate materials that contain the essential attributes meeting the required range specified in product design specifications. The second is to apply the technique of artificial neural network concept through the computational Matlab tool, to classify the short listed materials against certain other desirable preferences to obtain a final working list of candidate materials. The third module is to use database system software MySQL to accumulate data and to store them as knowledge base in the system. The block diagram of the total system is shown in Fig. 2.

### Expert Neural Classifier

Expert neural classifier executes high efficient learning for faster convergence. In this study, the output data of the expert system was mapped to the input layer of neural network for further classification of the selected materials. The artificial neural network module comprises a fully connected three layer feed forward network with a supervised training algorithm as the target is specified.

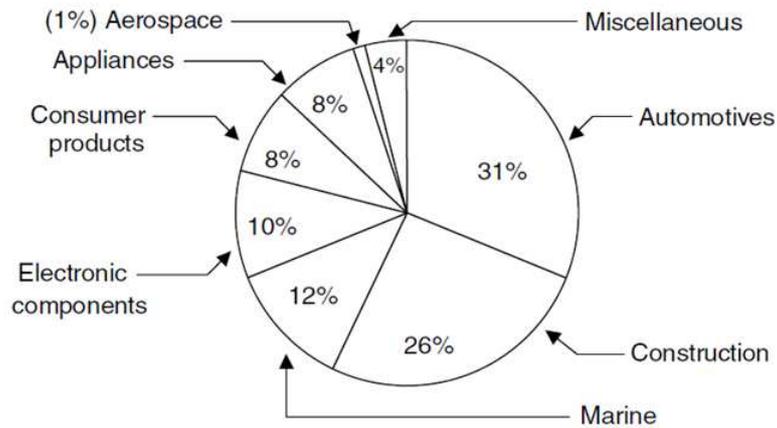


Fig. 1. Natural fibre composite usage in industries (Mohanty *et al.*, 2005)

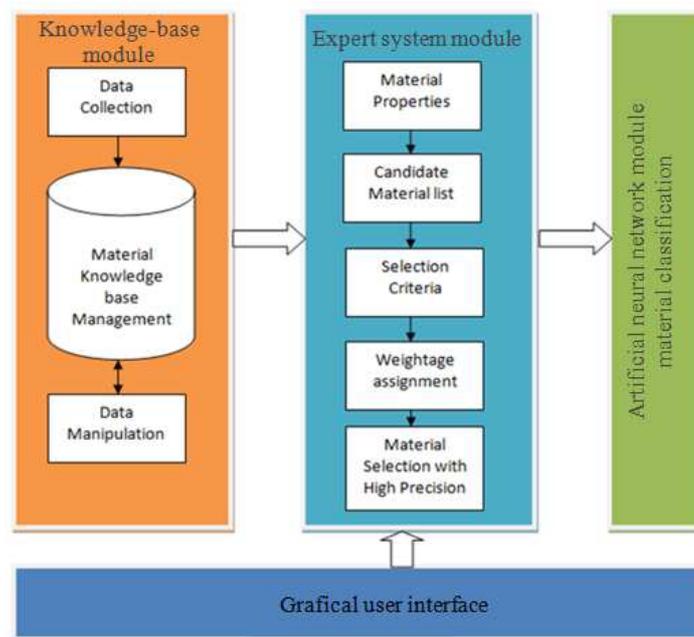


Fig. 2. Block diagram of the expert neural classifier system

The input layer consists of number of neurons equal to the attributes of candidate materials for classification; for this network three attributes (density, tensile strength and Young's modulus) are fed as the parameters for input layer. The target of the network was focused on the value defined by product design specification for automotive interior components (Ahmed Ali *et al.*, 2013). The outputs of the network would be the classification results. The flowchart in Fig. 3 clearly demonstrates the flow control in the Matlab programming with R2010b version using the toolbox of neural network. The network started with initialisation and data extraction from the expert system. The below mentioned command was used to import data by creating a file:

```
fid = fopen('private/materialdata.csv');
C = textscan(fid,'%f%f%f%s','delimiter',';'); % Import
data fclose(fid)
```

After importing the data to the file, the input data and target data had to be segregated and preprocessed in the form of matrices that can be used with the neural network. The next step was to create a feed forward network. The above input and target data were used to create the network with a unique number of hidden nodes. The syntax was shown as below:

```
net = newff(inputs,target,no.of hidden layers)
```

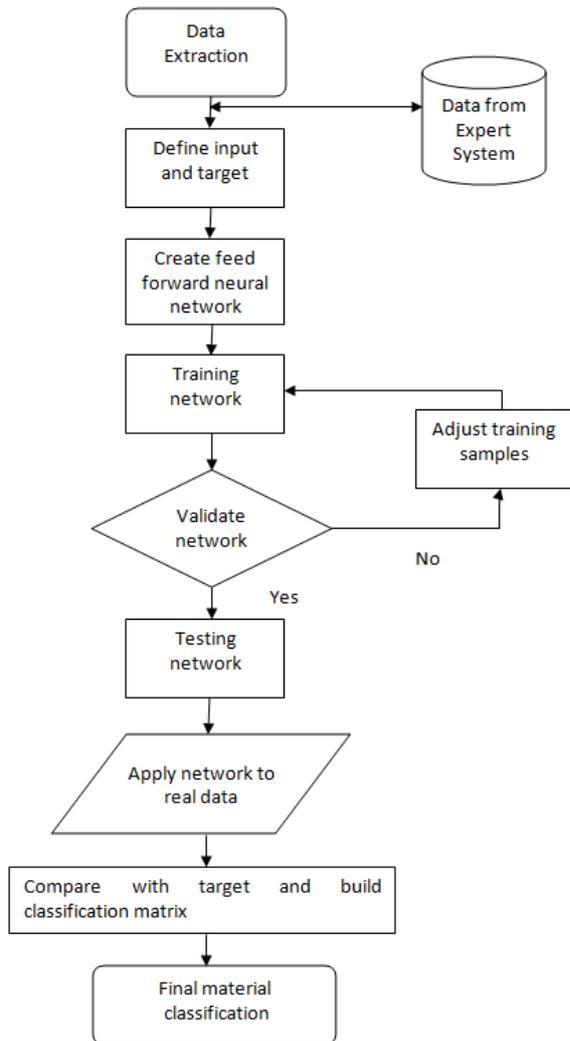


Fig. 3. Expert neural classifier flowchart

There are many criteria deciding the number of hidden layer to create a feed forward network and they are discussed in the next section elaborately. The next important step in the procedure of neural network was training the network with the input and target data. The training continued until the validation of the network was reached. The command to train the network is shown below:

$$[net, tr] = \text{train}(net, inputs, target)$$

The trained network was then tested with test samples. Next step was to apply the real data for the above constructed network and to record the output. Finally, the output was compared with the target and to build a classification matrix.

#### Knowledge Base Management System (KBMS)

In the expert neural classifier system the KBMS was the module to store the knowledge with higher

level of information that was represented in the easy manner to manipulate and store the material informations. Access to the knowledge base was performed through the expert system and was transparent to the user. The data manipulation was made easier with add, delete, update, save and search functions. The data required for ANN process were thereby extracted from knowledge base module which were retrieved from the expert system. The data set consists of three entities; density, tensile strength and Young's modulus of the candidate materials. In total of 120 data set of various natural fibre composites were used to train, validate and test the neural network system. Unlike other database, the NFC data are not much matured when compared with metals, alloys and plastics. As the research trends are newly focused on NFC material, it was difficult to retrieve the entire database of NFC from single source. Therefore, for our research purpose the data set were collected from books, published journals and the previous work of principal author and his co-workers (Sapuan *et al.*, 2011). The sample model of data set was shown in Table 1.

#### Feed Forward Algorithm

The feed forward neural network is also known as Multi-Layer Perceptrons (MLP) and it is most widely used model of neural network. Where the connections between the units do not form a directed cycle then it is referred to as a feed forward neural network. In feed forward neural network the connections are between two successive layers and the information flows in one direction, forward from the input layer to the output layer via the hidden layers. There are no cycles or loops in this network and no lateral connection between the neurons of the same layer (Sumathi and Surekha, 2010). The structure of 3 layers feed forward neural network with input layers, hidden layers and output layers are shown in Fig. 4.

#### Levenberg-Marquardt Algorithm

The Levenberg-Marquardt Algorithm (LMA) is an iterative technique to provide a numerical solution for minimizing a non-linear function. It is an optimization technique to solve large scale non-linear least square problems. The role of LMA behaves in between the Gauss-Newton Algorithm (GNA) and Gradient descent method. When the current solution is far from a local minimum and the result  $\lambda$  is large, the algorithm behaves like a steepest descent method; slow, but guaranteed to converge. When the current solution is close to a local minimum with small value of result  $\lambda$ , it becomes a Gauss-Newton method and exhibits fast convergence (Lourakis and Argyros, 2005).

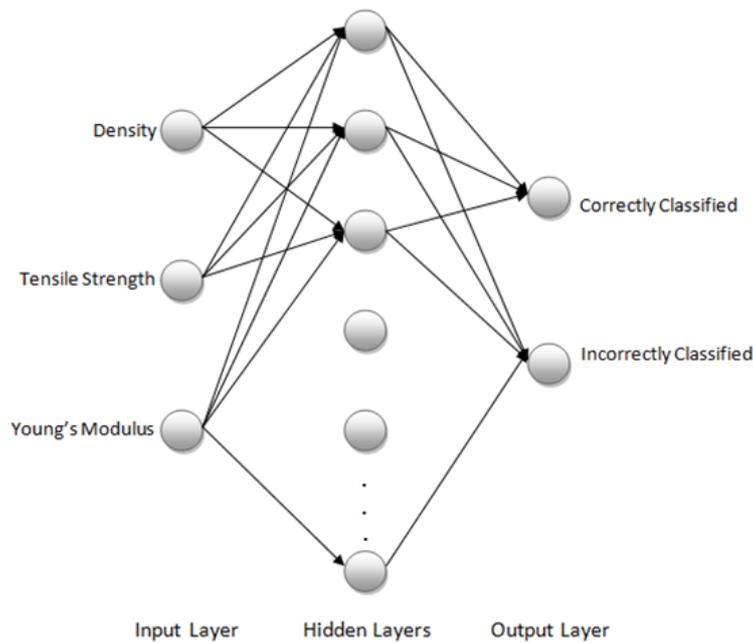


Fig. 4. A 3 layer feed forward neural network

Table 1. Model data set of natural fibre composites

Natural fiber composites	Density (kg/m <sup>3</sup> )	Young's modulus (GPa)	Tensile strength (MPa)
EFB + PP	875	0.900	18.00
Hemp 40% + PP	1076	6.800	52.00
Jute 40% + PP	1036	3.700	28.00
Kenaf 30% + PP	1027	3.800	27.00
Kenaf 40% + PP	1072	6.800	29.00
Kenaf 50% + PP	1120	7.500	35.00
Flax 36% + epoxy	1250	10.890	88.30
Flax 36% + PE	1250	8.350	71.60
Oil palm Empty Fruit Bunch (EFB) 13% + epoxy resin	1148	2.557	12.12
Oil palm Empty Fruit Bunch (EFB) 30% + polyurethane	1000	0.500	17.00
Pseudo-stem banana + epoxy resin	1280	1.890	45.57
Sisal 30% + PP	1032	3.800	30.00
Sisal 40% + PP	1044	5.500	34.00
Sisal + PVC	1284	4.200	10.00
EFB + PVC	1085	1.500	38.76
Bagasse + PVC	1465	0.700	27.00
Kenaf + PVC	1420	1.770	46.00
Vetiver grass 20% + PP	991	1.500	28.00
Vetiver grass (powder) 20% + PP	991	1.250	22.00
sisal + PE	1124	3.080	38.00
flax + PE	1250	8.350	71.60
EFB + PE	1086	0.520	13.00
Sugar palm + epoxy	1260	1.080	32.00

### Network Training

The neural network learns through an iterative process and adjusts the weight accordingly to train the network. In the network training procedure initially the network becomes more knowledgeable regarding the problem statement after several iteration of training. The objective of training is to end up with

desired output for all possible values of input feed to the network and also to minimise the error function.

### Trainlm

The trainlm is a training function of the network that updates weight and bias values according to Levenberg-Marquardt algorithm. In Matlab the LMA

is implemented by the function *trainlm*. The training parameters of *trainlm* are epochs, time, min\_grad, max\_fail, mu, mu\_dec, mu\_inc, mu\_max and mem\_reduc.

Validation parameters are used to stop the training vectors and to decide the performance of the network. In the neural network the mu controls how much the weights are changed on each iteration. It can be as low as  $10^{-6}$  and as high as 0.1. If the mu value is too small then it is expected that the network would converge too slowly. On the other hand if the value of mu is too large then it would cause the network to converge erratically and the network will exhibit chaotic condition (Somkuwar *et al.*, 2010). The parameter mu is multiplied by mu\_dec by each iteration. If mu becomes larger than mu\_max, the algorithm is stopped.

The training stops when any one of these condition triggers:

- The maximum number of epochs (repetitions) reached
- The maximum time limit exceeds
- Performance is minimized to the goal
- The gradient falls below min\_grad
- Mu exceeds mu\_max
- Validation check has reached max\_fail

### Mean Squared Error (MSE)

The common error function in the neural network to be minimized was the Mean Squared Error (MSE). It is a network performance function that measures the network performance accordingly to minimize the sum of mean squared errors. Like the perceptron learning rule, the mse is an example of supervised training. The network has an input and corresponding target output. As each input is applied to the network, the network output is compared to the target. The error is calculated as the difference between the target output and the network output. The performance of the network is calculated by average of the sum of these errors. The goal of training the network was to minimize the mse.

## Results

Great concern should be given in selecting number of hidden layers and the number of neurons in the hidden layer, as it can have a significant effort on the performance of the network. It is difficult to determine the number of hidden layers for particular learning process. These parameters are usually defined by trail and error method. However, it has been observed in general one hidden layer is sufficient in most ANN applications (Tan *et al.*, 2011; Trzaska and Dobrzanski, 2006; Smith, 1997). So, for

this network we decided to have one hidden layer. To decide the number of nodes in the hidden layer, few experiments are conducted ranging from 10 to 30 hidden nodes to study the reliability and performance (mean squared error) of the network. The performance value for different number of hidden nodes with the total number of epochs (repetition) and gradient values are shown in Table 2.

The above values are plotted in graphical representation for better understanding as shown in Fig. 5. It was observed that the artificial neural network with 15 nodes in hidden layers has the least performance value of 0.0353 with total number of 9 epochs and minimum gradient decent of 0.0121 was significantly efficient for this network. It can also be noticed that the network with 25 hidden nodes has the lesser performance value then 15 hidden nodes. Even though the performance value for 25 hidden nodes is 0.0259, the gradient value in bold denotes 0.0736 which is significantly higher then 15 nodes gradient value. Further analysis was carried out with network performance convergence graph to decide the number of hidden nodes for the network. When the network training performance was plotted with 25 nodes it had exposed a vast difference in the network convergence. While the network with 15 hidden nodes had significantly fast network convergence as shown in Fig. 9.

Similarly, the regression values are plotted for 10,15,20,25 and 30 hidden nodes as shown in Table 3 to further study the behaviour of these different hidden nodes. It can be observed that 15 hidden nodes have uniform data with regular interval. So, for this work the ANN with one hidden layer and 15 hidden nodes was selected to be efficient with favourable good result.

Therefore, for the current research work for classification of materials using neural network it was decided to have three input layers, one hidden layer with 15 nodes and two output layer. The architecture of the neural network is shown in Fig. 6.

After deciding the neural network architecture with definite structure the network is ready to be trained. The candidate materials were automatically divided into three distinct sets as training, validation and test sets. The training process would use largest set of data and teaches the network to learn the patterns present in the data set. Training continues until the network gradually improves on the validation checks. A final check on the performance of the network is made and the training stops on reaching the maximum validation checks. On completion of the training, the trained network would be tested with the testing samples. The test data provides a complete measure of network accuracy and guarantees that the network can be applied to real world data for classification.

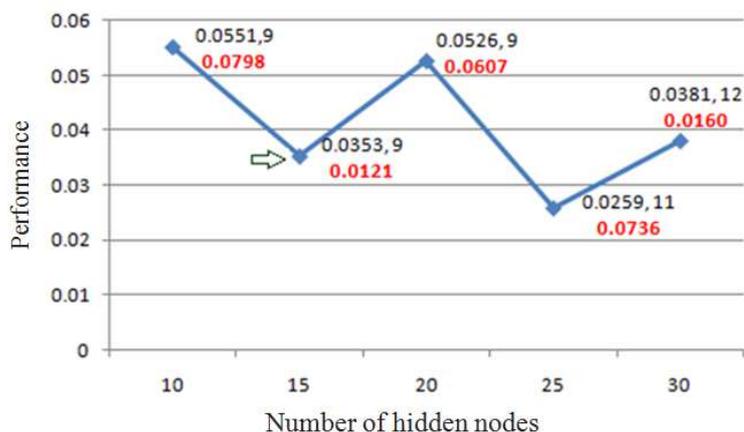


Fig. 5. Performance value verses number of hidden nodes

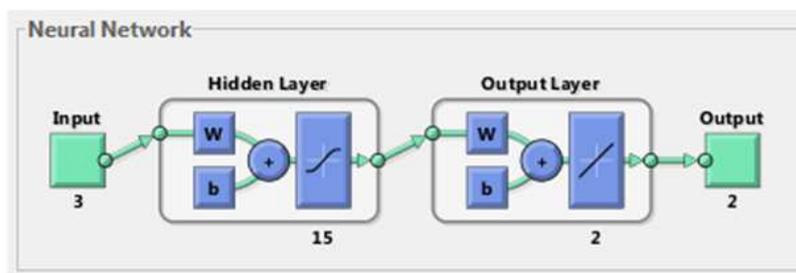


Fig. 6. Neural network architecture

Table 2. Performance of neural network for different number of hidden nodes

Number of hidden nodes	Total number of Epoch	Performance	Gradient
10	9 epochs	0.0551	0.0798
15	9 epochs	0.0353	0.0121
20	9 epochs	0.0526	0.0607
25	11 epochs	0.0259	0.0736
30	12 epochs	0.0381	0.0160

Table 3. Regression values of the neural network

Number of hidden nodes	Training	Validation	Testing	Overall
10	0.86523	0.99416	0.86445	0.88321
15	0.89655	0.85545	0.88918	0.88944
20	0.81713	0.91956	0.98757	0.85463
25	0.89679	0.95905	0.81018	0.89385
30	0.90251	0.86696	0.96329	0.90517

## Discussion

The network was executed with the set of knowledge base data of candidate materials from the expert system. Figure 7 shows the over all progress of the network. It clearly indicates that the training stops on reaching the maximum validation checks of 6. The number of epoch with 9 iterations and the performance (MSE) with 0.0353, gradient decent value of 0.0121 and mu value of 0.01.

Figure 8 shows the 3 layer neural network training state plot for network with 3 input nodes, 15 hidden nodes and 2 output nodes with combination structure as (3-15-2). The training stops when the validation parameter *max\_fail* reached maximum 6 validation checks at epoch 9 with the gradient decent value 0.012087 with reasonable *Mu* value 0.01 which would cause the convergence of the network fast. Because it could be expected that too small *Mu* value would cause the network to converge too slowly.

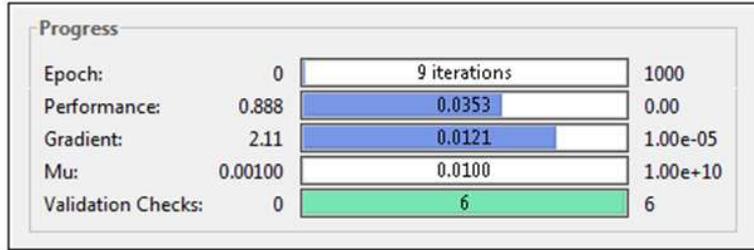


Fig. 7. Overall progress of the ANN

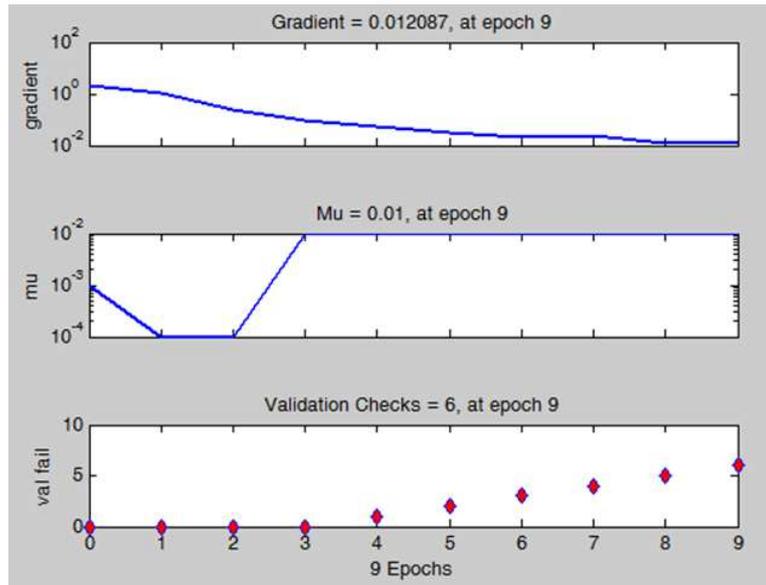


Fig. 8. ANN training state plot for 15 hidden nodes

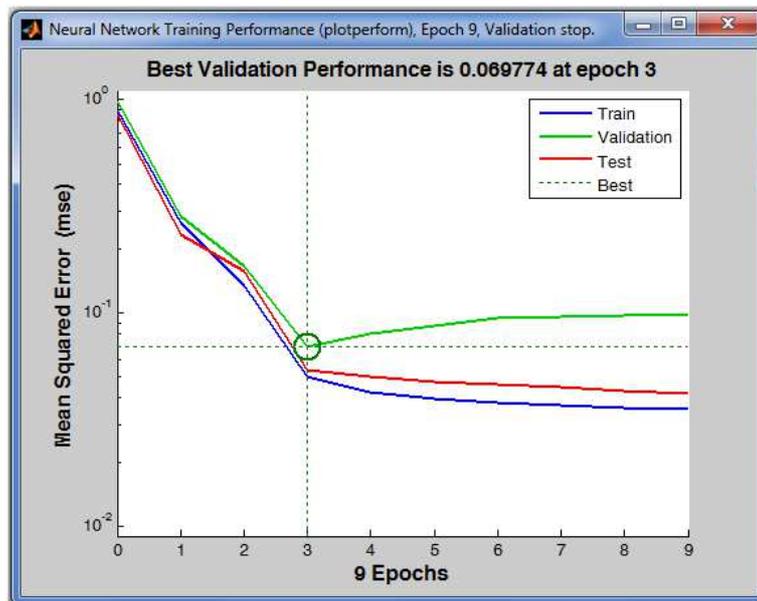


Fig. 9. Network training performance plot

### Network Training Performance

Neural network training performance plot i.e., plot perform of network is shown in Fig. 9. The value of training, validation and test performances returned by the function train of the network was plotted. The below figure shows that there is no much significant difference between the train and test curves, as they are more or less similar. This indicates there is no any major problem with the network training. In neural network training if the test curve had increased significantly before the validation curve increased, then there is a possibility that some overfitting might have occurred. Even though the training continues until 9 epochs, the best validation performance reached at epoch 3 with the value of 0.069774.

### Regression Analysis

The regression analysis was performed in ANN model after the network concludes training, testing and validation. It is a statistical process for estimating the relationships between the output and target of the network. The *plotregression* function takes two parameters (targets, outputs) values and plots the linear

regression of targets relative to the outputs. Figure 10 shows the regression plot of training, test, validation and over all regression. The small circle shows the data representation in the model. After the regression plot has been constructed, the diagnosis of the model is important to confirm the goodness of fit. Most commonly used coefficient of determination proof for goodness of fit includes R squared denoted as  $R^2$ , indicates how well the data points fit a line or curve. In the below figure the best fit was denoted as straight line. The dotted line indicates the outputs equal to targets ( $Y = T$ ). The relationship between the outputs and the targets are indicated by the Regression (R) value for every network procedure. If  $R = 1$ , this shows the exact linear Relationship (R) between outputs and targets. The R value would be rarely perfect in practice. In our model the network shows significantly acceptable R values near to one. The Training R value was 0.89655, validation R value 0.85545, test R value 0.88918 and over all R value equals to 0.88944. This proves the developed model and the network procedure of training, testing and validation are significantly acceptable.

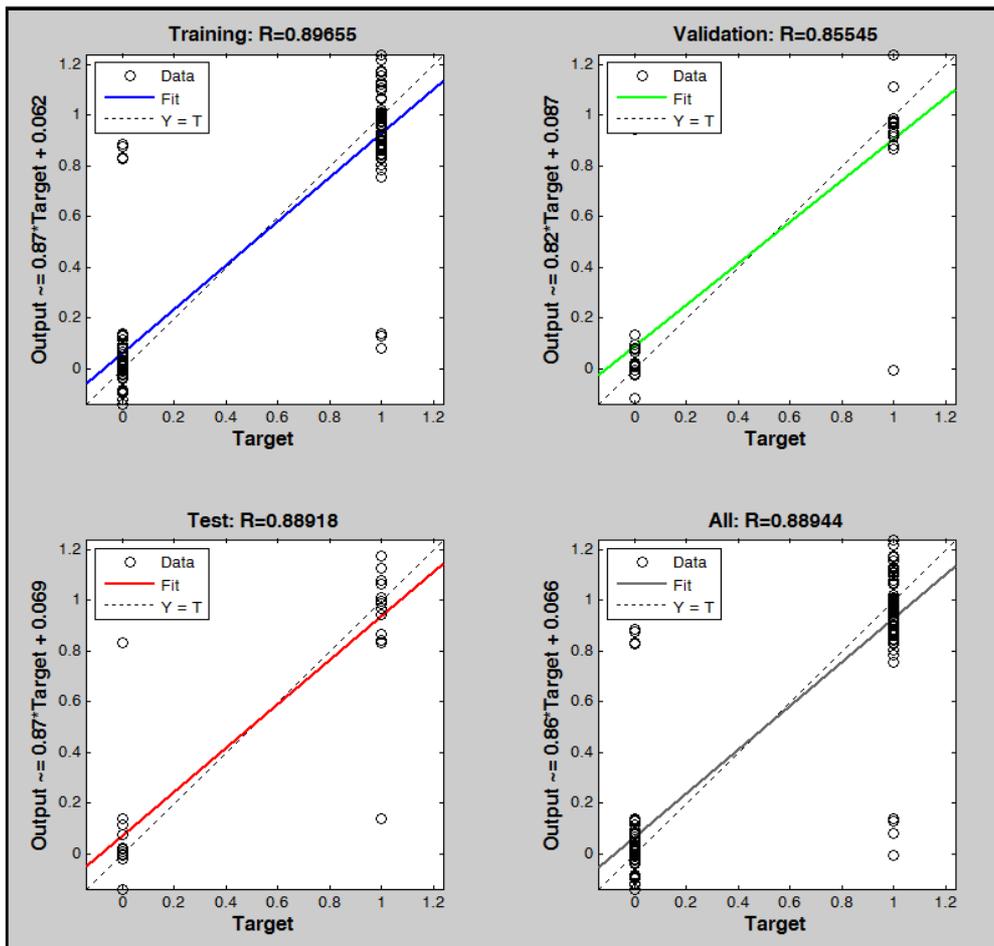


Fig. 10. Regression plot of network

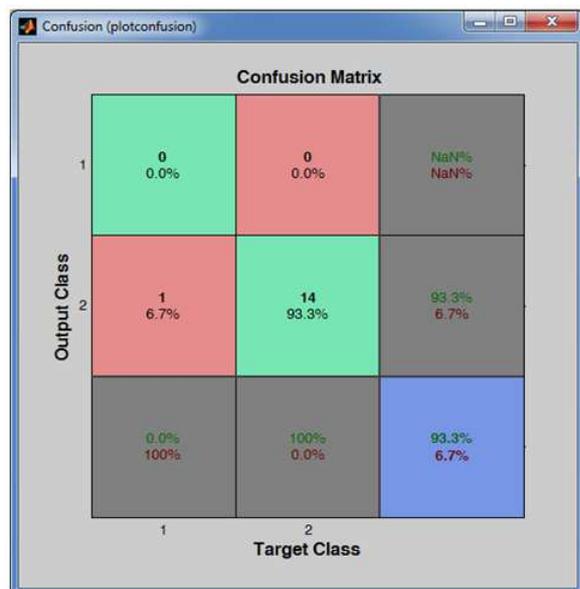


Fig. 11. Confusion matrix

### Confusion Matrix

The confusion matrix or an error matrix also known as contingency table is to identify the accuracy of the classification. In matlab programming, the toolbox neural network can plot confusion matrix. It is a specific table plot which allows the visualization of the performance of Levenberg-Marquardt supervised training algorithm. In this material classification, the system has been trained to classify the optimum material for interior automotive components from natural fibre composites. Ultimately, the below confusion matrix summarize the results of the testing algorithm of the expert neural classifier for further inspection. The classification accuracy and confusion (misclassification) was clearly shown in Fig. 11. The row of the matrix represents the instances in an output class, while each column represents the instances in a target class.

The possible conditions are positive and negative which takes the value true or false. Possible scenarios are true positive, false negative, false positive and true negative. The middle of the diagonal element represents correctly classified observations. So, the percentage of correctly classified was 93.3%, where the remaining 6.7% can be assumed as incorrectly classified.

Therefore, with all the above observations the artificial neural network model proves to be optimum classifier of materials. Nevertheless how large is the material knowledgebase, a perfect classification could be achieved by the proposed expert neural classifier system.

### Conclusion

This work presents the application of artificial neural network with feed forward network and Levenberg-Marquardt training algorithm to classify the natural fibre

reinforced composite materials. The classification was made for natural fibre composite materials with high precision. In future the system can be extended with medium and low precision and also guarantees that the ANN is good to integrate with expert system and basically can handle huge amount of data. The ANN with 15 hidden nodes shows best result and the classification accuracy was 93.3%. The research finding proves that ANN is capable to be implemented in materials selection and classification.

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### Author's Contributions

**Basheer Ahmed Ahmed Ali:** Principal author who conducted the research work, data collection and contributed to the writing of the manuscript.

**Mohd Sapuan Salit:** Advised with expertise and designed the research plan and approved to complete this manuscript.

**Edi Syams Zainudin and Mohamed Othman:** Co-supervisor of this research work who provided technical support for the manuscript.

### Ethics

This manuscript was the original research work carried out by the principal author and his supervisory committee. The authors declare that this manuscript was not submitted/accepted elsewhere for publication and free from all ethical issues.

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