Implementing Neural Network for Damage Severity Identification of Natural Kenaf Fibre Composites

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Abstract: The emergence of natural fiber as a potential alternative for glass fibre replacement has seen various development and investigation for various applications. However, the main issue with the natural fibre reinforced composites is related to its susceptibility to impact damage. This paper presents a preliminary case study of damage identification in Natural Fibre Composites (NFCs). The study involves a simple experiment of impact on a NFC panel. The strain data are measured using piezoceramic sensors and the response signal was investigated. Then an effective impact damage procedure is established using a neural network approach. The system was trained to predict the damage size based on the actual experimental data using regression method. The results demonstrated that the trained networks were capable to predict the damage size accurately. The best performance was achieved for an MLP network trained with maximum signal features, which recorded the error less than 0.50%.

Introduction

Current trend of research have stressed out the importance of creating a sustainable and viable environment conditions. Due to this environmental issue, various researchers have proposed various potential of natural fibres as the potential replacement for current synthetic fibres. With low cost and high specific mechanical properties, natural fibres represent a good, renewable and biodegradable alternative to the technical reinforcing fibres presently available. In structural applications and infrastructure applications, natural fibre composites (NFC) have been used to develop load-bearing elements such as beam, roof, multipurpose panel, water tanks and pedestrian bridge. While in automotive industries and productions of non-structural elements NFC have been used to produce mirror casing, paper weights, projector cover, voltage stabilizer cover, mail-box, helmet and roof [1]. However, Natural Fibre Composites (NFC) tend to fail by most common types of damages in fibre composites such as delamination, matrix cracking, fibre breakage, fibre pull out and fibre–matrix de-bonding. Among the various types of damage, delaminationis probably the most frequently occurring damage due to their weak transverse tensile and interlaminar shear strength as compared to their in plane properties. Subsurface delamination may be caused by accidental impacts by hard objects, crack in matrix materials, broken fibres and fatigue loading of the structure. The presence of this sort of damage can severely degrade the mechanical properties of composite structures, and if it is not detected in the incipient stage, it may result in a catastrophic failure of the structure. In order to prevent catastrophic failures, structural health monitoring (SHM) systems have noticeably become employed recently [2–5].

Numerous damage diagnostic methods for structures have been proposed, and most of them employ either a parametric method based on modelling of the structure or a non-parametric method such as an artificial neural network (ANN). Neural networks have been drawn considerable attention due mainly to their ability to approximate an arbitrary continuous function and mapping. ANN has been used in the fields of failure prediction, delamination identification, and crack detection and in the modelling of manufacturing processes as well as the mechanical behaviour of these materials. It is able to learn by example and does not have to know the theory behind a phenomenon [6]. This quality is useful in describing problems where the relationship between
inputs and outputs are not clear enough or the solutions are not easily formulated in a short time. These networks have been used successfully to model the behaviour of engineering problems. Chakraborty [7] predicts the presence of embedded delamination in fibre reinforced plastic composite laminates by using back-propagation Neural network (BPNN). The network has been tested to predict the presence of delamination along with its shape, size and location. According to their results the network can predict reasonably well when tested with unknown data set and can learn effectively the shape, size and location of a delamination embedded in the laminate. Simulated data has been used for training and testing the network and it found that the results are good agreement. Jeyasehar and Sumangala[8] introduces ANN approach using feed forward that learns by back propagation algorithm to assess damage in pre-stressed concrete beams from natural frequency measurement. It has been observed that the average of predicted damage levels obtained for various test data sets are predicted correctly with a maximum error of just 8.9%. This maximum error occurred when the ANN trained with two inputs namely, applied load and natural frequency. This is justified by the fact that the ANN can learn better and predict better when it is trained with more data. While for mix of static and dynamic data, it has been demonstrated that for different applied loads on a pre-stressed concrete beam, damage level can assess with less than 10% error. Yuan et al. [9] investigated the presence and extent of damage for delamination and impact damage in composites using Kohonen neural network. Delamination is simulated by embedding a Teflon slice with 0.1 mm thickness into the composite structure while impact damage is generated by impacting a healthy specimen with a hammer. The network has been tested to predict five damage modes which are defined as P1, P2, P3, P4 and P5. Then these different damage modes are separated to different locations on the map. The result showed that, the network able to separated different damage mode successfully. Worden et al. [10] and S. Mahzan [11] in their research, implemented neural network for classification and regression problem. It was found that impacts can be located on complex structures such as aircraft component using features from strain wave propagation in the structure. Whereas the neural network trained for the location estimate by providing coordinates.

Although a previous publication have investigated thoroughly the diagnostic methods based on neural network, however little information concerning the neural network for NFC has been reported. The aim of the current paper is to investigate the ability of neural network to predict the actual damage size with the estimated damage size using piezoelectric (PZT) sensors to detect damage in NFC.

Multilayer Perceptron Neural Network.

1. **Number of nodes in the input and output layer.** The input and output variables were determined, 10 inputs are: Strain data from sensors S1 to S10, whereas the 1 output is the damage size. Thus, the number of the nodes in the input layer and the output layer were determined, with 10-dimensional input vector and 1-dimensional output vector.

2. **Hidden layer.** Hidden layers can be single, double or multiple layers. A feed forward network can reflect all continuous functions. When a large quantity of hidden nodes of a hidden layer cannot improve the network’s performance, another hidden layer may be added. In consideration of the prolonged learning time of the network possibly caused by the addition of a hidden layer, single hidden layer is chosen in this paper.

3. **Number of hidden layer nodes (hidden nodes).** The method of trial and error was adopted in the experiment to determine the number of hidden nodes. Therefore, in consideration of the number of hidden nodes and the speed of error convergence, the network’s structure with 20 hidden nodes was adopted as the neural network model. Therefore, the number of nodes of the input and output layer, the number of hidden layers and the number of hidden nodes in the neural network model were determined as 10, 1, 1 and 20 respectively. The network was trained to estimate damage size for a single signal feature as the input and the MSE was defined as
Sample Preparation. The selected raw material of the fibre for this research was kenaf short fibre and the matrix was selected from epoxy resin group. The dimensions of the kenaf fibre composite boards were 300mm (L) ×300mm (W) and 3mm thickness. The composites with fibre loading 10% of volume fraction were fabricated using compression technique. The internal surfaces of the mould were sprayed by a release agent (Silicon), in order to facilitate easy removal from mould. Initially, epoxy resin and hardener were mixed with ratio 2:1 to form a matrix. Then the short kenaf fibres and matrix was mixed together using a mixer for 10-20 minute to disperse the fibres in the matrix. After that, the mixture was poured into the mould and the mould was closed before manual compression took place and it was left about 24 hours for curing at room temperature. Care was taken to evenly distribute the fibres in the mould to ensure a uniform sample since natural fibres have a tendency to clump and tangle together when mixed. Lastly the sample was taken out of the mould and post-cured in the air for another 24 h.

Experimental Set Up. An impact hammer, as used for modal testing, was applied to produce impacts on the natural fibre composite plate. The experiments were conducted on a laboratory, where the plate was positioned on foam without any mechanical constraints. PZT sensors were chosen for detecting the impact, ten for each plate. The diameter and thickness of each sensor was equal to 6.5 and 0.25 mm, respectively. The sensors were placed at ten different positions on each plate in order to sample responses at different distances from the impact as shown in Fig. 1. The DEWE soft oscilloscope was used to capture and display all strain data from the impact events with a sampling frequency of 5 kHz.

Results and Discussion

A series of low-velocities, low-energy impacts were performed at different force as for 40 plate as illustrated in Figure 1. The resulting strain waves of 2 s were acquired by sensors S1 until S10. The PZT sensor signals for sensor S1 until S10 are recorded during impact and the maximum peak, minimum peak and peak to peak value are illustrated in Figure 2 as an example. Then the data were analysed for each impact damages.

Neural Network Results. The input to the network consisted of a three signal features selected from the strain data, namely the maximum peak, minimum peak, peak-to-peak. The overall impact data collected in the experimental tests were divided into three different sets. The training data set used data features (256 points) validation set (65 points) and a testing set (65 points). The damage severity analysis using the MLP involved three different steps. Firstly, the network was trained

\[
MSE = \frac{\sum_{i=1}^{N} (A_i - \bar{A}_i)^2}{Area \ of \ structure \times N} \times 100\%
\]

where, 

- \( \bar{A}_i \) = actual damage size 
- \( A_i \) = predicted damage size 
- \( N \) = Total no of impacts
using the training data set as the inputs, and the connection weights were iteratively adjusted until
the network produced the best match to damage size. Then second step validated the network using
the validation data set. At this stage, the most suitable number of hidden layers and hidden layer
nodes was determined for each network. The network was trained to estimate size of damage for a
single signal feature as the input and the error results are given in Table 1.

Table 1. Damage estimation percentage error for the ANN-based regression procedure

<table>
<thead>
<tr>
<th>Features</th>
<th>Percentage error [%] (Training)</th>
<th>Percentage error [%] (Validate)</th>
<th>Percentage error [%] (Testing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum peak</td>
<td>0.2</td>
<td>0.11</td>
<td>0.36</td>
</tr>
<tr>
<td>Minimum peak</td>
<td>1.99</td>
<td>1.6</td>
<td>2.4</td>
</tr>
<tr>
<td>Peak to peak</td>
<td>0.53</td>
<td>0.34</td>
<td>0.91</td>
</tr>
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</table>

These results show that the overall trend for the estimated damage size agreed well with the
actual damage size for all the time domain features investigated. However, a little difference can be
observed. These differences were analysed using Eq. 1. The results demonstrate that the best
network performance was obtained when maximum peak feature was used (total error less than
0.5%) while the worse performance was achieved for the minimum peak feature (total error more
than 2%).

Fig. 2. Example of minimum peak, maximum peak and peak to peak value taken for each strain
signal

(a)

(b)
Conclusion

This study shows that the multilayer perceptron neural networks can efficiently define the damage size in NFC panel, for regression networks. Based on the results and preliminary success in natural fibre composites development using kenaf fibres mixed with epoxy, so the other natural fibre can be used as a main raw material in signal processing method. The use of neural network as an intelligent health monitoring system offers the advantages of processing speed and multiple input processing. It can warn of damage initiation and severity. Such an assessment system would provide better structural management and avoid catastrophic failure.

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