Advanced Materials Research Vol. 911(2014) pp60-64

doi:10.4028/www.scientific.net/AMR.911.60

Damage Size Classification of Natural Fibre Reinforced Composites using Neural Network

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Keywords: Confusion matrix, Natural fibre reinforced composite, damage, multilayer perceptron neural network.

Abstract. Damage classification is considered as an important feature in pattern recognition, which led to providing significant information. This research work explores damage size classification for several impact events in natural fibre reinforced composites, which is based on the information provided by the ten piezoceramics (PZT) sensors. An Impact event produced strain waves which several data features were obtained through the response captured. An effective impact damage classification procedure is established using a multilayer perceptron neural network approach. The system was trained to predict the damage size based on the actual experimental data. The data features were mapped into five output class labels, presented as a target confusion matrix. The classification results revealed that the damage sizes were successfully mapped according to its respective class, with the peak to peak feature gives the highest classification rate at 98.4%.

Introduction

Great concern about global warming issues has led to researcher to transform interest in a more sustainable use of natural fibres in composite materials. The new markets for such fibres are not only provide solutions to some environmental problems but may also offer a potentially bright future for the mass consumption of these resources. Therefore more researches are crucially needed to refresh the use of natural fibres in order to transform natural resources into new industrial materials while promoting greater use of green renewable resources. Furthermore, the future trend of extreme light-weight car design will further enhance the potential application of natural fibre composites in automotive structural parts applications [1]. Automotive components made from light-weight natural fibre-reinforced composites can significantly reduce overall vehicle weight, which results in energy saving and low emission to the air. Though automotive parts made from natural fibre-reinforced polymer composites have many benefits as compared to glass fibres, there are still several major technical issues which need to be addressed before the automotive industry gains full confidence to enable wide-scale acceptance, especially in the application of automotive exterior parts. Composite materials are more susceptible to impact damage than similar metallic structures. If a composite part is subjected to normal low-velocity impact of sufficient energy, it may create damage. Understanding the damage involved in the impact of composite targets is important in the effective design of a composite structure. For these reasons, numerous experimental and analytical techniques have been developed to study the dynamic response of composite structures subjected to transient dynamic loading [2-7].

Conventional damage assessment methods are naturally direct process methods, proceeding linearly from cause to effects. These methods involve in constructing a mathematical model for the structure. Then, a model to clarify the structural behaviour and a correlation between the specific member damage condition and changes in the structural response is established. An artificial neural network (ANN) is a viable solution which is effectively be used to assess the damages. It has been drawn considerable attention mainly due to their ability to approximate an arbitrary continuous function and mapping. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANN with their remarkable ability to derive meaning from complicated data can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [8]. A trained neural network can be thought of as an ''expert'' in the category of information it has been given to analyse. Lerner et al. [9-10], implemented Sammon's mapping, an auto associative NN (AANN) and multilayer perceptron (MLP) feature extractor for five real world databases consisted data sets of three classes, each class consists of 100 (50 for the iris data) patterns with dimensions of 64 (chromosome 4 (chromosome (geometrical)), 36 (satellite), 79 (RAE) and 4 (iris). The result revealed that MLP give the highest classification accuracy as compared to other features. Worden et al. [11], demonstrated the ability of neural network to detect impact location using regression, classification and combination of both method for a composite aircraft component. In regression method, the network was trained to predict the x and y coordinates of the impact when presented with the features extracted from the time-varying strains. In classification method, the damage was located within substructures. The problems were then converted where into a classification problem within each substructure. The neural network is trained as a classifier and has one output assigned to each class which is three outputs. The result for regression method showed fairly good agreement between the predicted and measured x and y coordinates, respectively. On the other hand, classification method provides a high classification rate and only makes mistakes on impacts which are near to the borders of the class regions.

It has been observed from the earlier works that neural networks has attracted attention due to their capabilities including pattern recognition, classification and function approximation is well documented in the literature. So the work presented herein attempts to develop an artificial neural network (ANN) for detection the extent of damage in NFC using classification method to produce classification rate and confusion matrix. Also, to highlight the viability of using this NFC material and the associated signal analysis that can be employed to detect the presence of damage extent.

Multilayer Perceptron Classification Network Results

The architecture for this MLP classification network was restricted to 10 input nodes. A single hidden layer with 20 hidden nodes was adopted as the neural network model with five output nodes for the five possible damage classes. 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. Softmax activation functions were used by the five output nodes to ensure that their outputs always summed to unity, so it could be viewed as posterior probabilities for the five classes. Each data sample can therefore be assigned to the output class that has the highest posterior probability. The softmax activation function is given by eq. 1

$$y_k = \frac{\exp(x_j^{(k)})}{\sum_j \exp(x_j^{(k)})} \tag{1}$$

where,

k is the output value index

X_j is the summed input into output value y_k

Confusion Matrix

A confusion matrix is a matrix which indicates true classes (the actual damage size) represented by the matrix row, whereas the matrix column represents the classification classes (predicted damage size). The element M[i][j] gives the number of times that a class i object was assigned to class j. The actual damage size is described by the class'*i*' (i=1, 2,3,4 and 5) and the predicted damage size is given by the class'*j*'(j=1, 2,3,4 and 5), the M_{ij} element of the confusion matrix is increased by '1' the sum of all M_{ij} elements is equal to the number of impact tested. The diagonal elements indicate correct classifications made for each class, and the off-diagonal elements show the errors made.

Sample Preparation

The investigation employs the chopped kenaf fibres as the natural fibre and the epoxy as the resin matrix. The dimensions of the kenaf fibre reinforced composite panel 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 in order to facilitate easy removal from the mould. Initially, epoxy resin and hardener were mixed together with ratio 2:1 to form a matrix. Then the chopped kenaf fibres and matrix was mixed together using a mixer for 10-20 minute to disperse fibres in the matrix. The mixture was poured into the mould and closed before manual compression took place. The sample was left to cure for about 24 hours at room temperature. Finally the panel was taken out of the mould and post-cured in the air for another 24 hours.

Experimental set up

An impact hammer was used to produce impacts on the NFC panel. The experiments were conducted at a laboratory, where the panel was positioned on foam without any mechanical constraints. PZT sensors were chosen for detecting the impact and 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 *DEWEsoft* oscilloscope was used to capture and display all strain data from the impact events with a sampling frequency of 5 kHz.

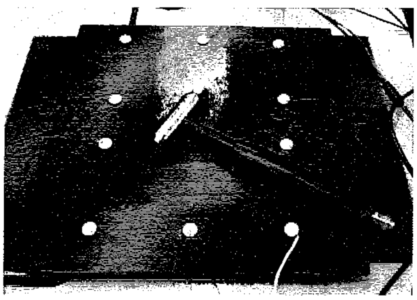

Fig. 1: Experimental set-up for low velocity impacts

A series of low-velocities, low-energy impacts were performed at different force as illustrated in Fig. 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 were analysed for each impact damages. Table 1 shows the classification and the range of damage size assigned to each class. The class were selected based on amount of damage size assessed in the experimental work.

Table 1 Damage and code classification

Classification of Damage	Range of damage size (cm)	Class
No damage/Scratches	0.6<DS< 1.5	1
Small cracks	1.5<DS<3	2
Moderate Cracks	3<DS<4	3
Intermediate Cracks	4<DS<5	4
Severe Cracks	5<DS	5

Results and Discussion

The MLP analysis involved four different signal features which is maximum peak, minimum peak, peak to peak and the combination of all the features. Fig. 2 depicts the MLP classification results for the signal features. The feature that created the best highest classification rate was observed when the network used peak to peak feature with 98.4% as shown in Fig. 2 (c). Then it was followed by the combination of all features with 97.5%, demonstrated in Fig. 2 (d). The lowest classification rate was identified by minimum peak feature with only 86.9% which is below 90% as compared other features.

	Predicted Class				
True Class	C1	C2	C3	C4	C5
C1	78	6	0	0	0
C2	6	54	0	0	0
C3	0	3	75	0	0
C4	0	0	0	66	0
C5	0	0	0	0	78

(a) Classification rate 95.9%

	Predicted Class				
True Class	C1	C2	C3	C4	C5
C1	84	0	0	0	0
C2	9	51	3	0	0
C3	0	0	75	0	0
C3	0	0	3	63	0
C5	0	0	0	0	78

(b) Classification rate 86.9%

	Predicted Class				
True Class	C1	C2	C3	C4	C5
C1	84	0	0	0	0
C2	3	60	0	0	0
C3	0	0	75	0	0
C3	0	0	3	63	0
C5	0	0	0	0	78

(c) Classification rate 98.4%

	Predicted Class				
True Class	C1	C2	C3	C4	C5
C1	252	0	0	0	0
C2	9	176	4	0	0
C3	0	1	220	4	0
C3	0	0	4	193	1
C5	3	0	0	1	230

(d) Classification rate 97.5%

Fig.2: Damage size classification results obtained for (a) maximum peak, (b) minimum peak, (c) peak to peak, and (d) combination of all features

Conclusion

An ANN was used to classify damage size using impacted area obtained from low velocity, damage inducing impact experiments performed on NFC panels. The classification problem involved defining five classes for damage severity when the damage occurred. Using the strain profiles as inputs feature, feed forward back propagation neural network was successfully trained and tested the data according to their classes. All the features assigned, get high classification rate, more than 90% whereas, only minimum peak feature get the lowest classification rate which is below 90%. Generally, a larger training data will generate more classes may increase accuracy for extension of this future work.

Acknowledgements

The author gratefully acknowledges the financial support provided by Universiti Tun Hussein Onn Malaysia (UTHM), Johor, Malaysia under a Grant ERGS, E009.

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