Review on prediction and detection of failures in laminated composite materials using neural networks

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Abstract

Reliable failure detection and prediction in laminated composite materials are critical for the utilization of these materials. There are many quantitative techniques that have been successfully researched and implemented for such kind of failure detection and prediction. Most of these techniques are based on non-destructive methods for data collection and quantified by using neural networks for prediction and detection. In this paper a review on failure detection and prediction on laminated composite materials by using neural networks is presented. The non-destructive techniques considered are limited only to natural frequencies, electric conductivity, and lamb waves. Initially, the paper gives a brief introduction to every technique followed by summaries and evaluations for some selected works related to the technique.

1 Introduction

In recent years, there has been a rapid growth in studying and using laminated composite materials (*LCMs*) in all types of engineering structures (e.g. aerospace, automotive, off-shore, underwater structures, medical prosthetics, and sports). *LCMs* are fabricated by stacking plates or plies of composite materials together to provide materials with superior mechanical properties over constituent counterparts (e.g. materials with high strength and low weight). However, in practical situations, various cases of material failures or damages may occur during fabrication processes or in-services. The failure process of *LCMs* is quite complex, involving both intralamina damage mechanisms (e.g. matrix cracking and fiber fracture) and interlamina damage (e.g. delamination between plies and debonding between fibers and matrix). For example, in a fiber reinforced plastic laminate (*FRP*), a delamination may occur between plies and propagate, eventually, leading to catastrophic failure of the structure. This may happen due to a tool dropped during maintenance, a bird or hail strike in plain flight, runway debris striking during takeoff or landing, or anything else. Such delamination may go undetected during testing and lead to catastrophic damage in the future [1, 2].

Detection and prediction of failures in *LCMs* are complex issues for visual inspections and need not only rational techniques of analysis, but also techniques to classify the failures by predicting their sizes, shapes, and locations. The presence of such failures produce changes in physical properties of the material, which may decrease the system reliability by decreasing the material's strength and stiffness [3]. Non-destructive evaluation (*NDE*) or non-destructive testing (*NDT*) is defined as a technical method to inspect materials for failures without destroying them (the two terms *NDE* and *NDT* are used interchangeably in this paper). *NDE* is similar to a shopper, when uses smell to specify the ripeness of a peach. Traditional *NDE* approaches (e.g. natural frequencies, *C*-scanning, electric conductivity, optical conductivity, acoustic emission, and lamb waves [1, 3–5]) were applied as operator-dependent, subjective, and qualitative methods. These approaches were widely accepted in major engineering communities until doubts have been raised and intensified concerning the compromise between detection precision and practical reasonability that these methods can offer [6]. Generally, qualitative approaches are not enough to achieve good failure prediction or detection in many cases, (e.g. failure detection in three-dimensional composite structures with non-negligible interlaminar position) and there is a real need for quantitative approaches so as to predict such kind of failures. This still remains a challenge to the researchers due to the absence of efficient prediction approaches. Fortunately, neural network (*NN*) is a quantitative approach that is widely employed for pattern recognition, classification, function approximation, signal processing, and system identification. Neural networks (*NNs*) have demonstrated an uncontroversial capability for complex damage detection. A combined computational mechanics with *NNs* has been extensively used to predict failures in laminated composite materials [7].

In this paper the failure prediction and detection in *LCMs* using *NN* are reviewed. Initially, general description and different types of *NN* are presented. Then a summary of previous work of some selected topics, which use *NN* as a prediction or detection method of failures in *LCMs* is given.

2 Neural Networks

Neural network (*NN*) is a technique in artificial intelligence, like expert systems, genetic algorithms, fuzzy logics, and Bayesian networks that simulates a biological brain. It has been widely used in different research areas like medicine, business, and engineering. It has been successfully implemented in many applications, e.g. speech recognition, diagnosis of hepatitis, recovery of telecommunications from faulty software, image recognition, and detection of failures in laminated composite materials. The popularity and success of the *NN* in modeling non-linear problems and its robustness for noisy environment make it an ideal choice for such kind of applications [8–10].

The purpose of an *NN* is to extract patterns and detects trends from complicated or imprecise data that are too complex to be noticed by either humans or other computer techniques.

There are many different structures, training procedures, and testing procedures for *NNs*. But generally, an *NN* consists of potentially large number of simple processing elements known as *nodes* or *neurons*. A neuron influences other's behavior through a weight. Each neuron simply computes a nonlinear weighted sum of its inputs, and transmits the result over its outgoing connections to other neurons [11]. The behavior of the network depends largely on the interaction between these neurons. The network consists of several *layers* of neurons, these are *input* layer, *hidden* layer or layers, and *output* layer as shown in Figure 1. The input layer takes the input data and distributes them to the hidden layer(s) (the user cannot see any of the input or output of a hidden layer). The hidden layers do all the necessary computation and transmit the results to the output layer, which shows the final result to the user.

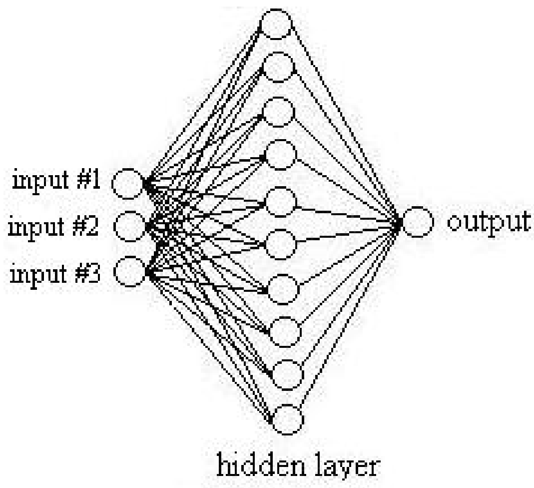

Figure 1: A simple neural network with 3 layers (input, hidden, and output)

The network is not strictly programmed, but passes through important information phases known as training and testing phases. In the training phase the network is given many cases of inputs along with the true outputs. The system learns by adjusting the weights of relative impact of inputs to outputs, and trying many combinations of weights until a good fit to the training cases is obtained. Then the resulting network can be used to evaluate future cases, which yields a classification results [12, 13].

NNs are characterized by their structure, weights, and the training technique used to specify their weights. *NNs* can be classified into several types based on the learning technique used, and the selection of a type is mainly dependent on the problem to be solved. These networks can take several forms, such as feed-forward (*FF*) *NNs* , backward propagation (*BP*) networks, Kohonen networks, radial basis function networks, Hopfield networks, and Elman networks [14, 15].

In *FF NN*, the activations of the input units are set and then propagated through the network until the values of the output units are determined.

A typical *BP* network has at least one hidden layer. There is no theoretical limit on the number of hidden layers, but typically there is just one or two. Some work has been done, which indicates that a maximum of four layers (one input layer, two hidden layers, and one output layer) are required to solve problems of any complexity [16]. However, it has been shown that it is possible to model many systems with a single hidden layer [17]. A *BP* calculates the weight values by iterative steps [2, 16, 17]:

- One input case is applied to the network and the network produces some output based on the current weights of the network. Initially, the weights are assigned at random.
- The calculated output is compared to the correct output and the error of the output is calculated.
- The error value is propagated backwards to the network and the weights are adjusted in each layer according to this error.

The whole process will be repeated for all training cases many times until the overall error drops to a zero value or gets lesser than a pre-specified threshold. Then the network passes through testing process to determine the accuracy of the network before the deployment. Trained *NN* can be treated as an expert in the category of information provided to analyze. This expert can then be used to predict the output of new given situations of interest.

Some of the main advantages of *NN* can be summarized as follows [18]:

1. Adaptive learning: an *NN* can adapt itself to predict unseen cases based on the data given for training.
2. Self organization and representation: an *NN* can form its own organization or representation of the information it receives during the learning process.
3. Parallel computation: an *NN* computations may be carried out in parallel, and specific hardware devices have being manufactured for this purpose.
4. Fault tolerance: partial destruction of a network leads to the corresponding degradation of performance, but some network capabilities may be retained, which may still give acceptable results.

Disadvantages of *NNs* include its black box nature, greater computational burden, and the empirical nature of model development.

3 Previous Work

All of the *NDE* techniques, which used with *NNs* to quantify the detection and prediction of failures in *LCMs* have advantages and disadvantages in terms of accuracy, expense, and level of instrumentation required. Most of them require sensing of strains and acoustic waves by using embedded optic fibres or transducers mounted at the material surfaces [19]. Lamb wave (*LW*) methods have re-emerged as one of the most reliable techniques that are capable of propagating relatively long distances in *LCMs* plates [20, 21]. Alternatively, electric conductivity is also widely implemented for the same purposes. This method has a long history in geology and biomedical applications in which an electric current is applied and the electric potential is recorded at monitoring electrodes around the area of study. The successful *NDT* techniques for small laboratory specimens, such as radiographic detection and *C*-scanning, are impractical for large components. Natural frequency methods are simple to implement on structure of any size. Structures can be excited by external shakers or embedded actuators, and embedded strain gauges or accelerometers can be used to monitor the structural dynamic responses [22].

It is very difficult if not impossible to review all of the *NDE* techniques in a single paper. Therefore, in this paper the review is restricted to summarize only some selected topics which, considered the implementation of natural frequencies, electric conductivity, and lamb waves as non-destructive techniques.

3.1 Natural Frequencies

The presence of damage in *LCMs* causes changes in the physical properties of the material, which does not affect the mass distribution but reduces the stiffness of the structure and leads to changes in modal parameters (notably frequencies, mode shapes, and modal damping factors). It has also been shown that natural frequencies are sensitive to the size, location, and shape of the damage such as delaminations in structural components [23–26]. Therefore, natural frequencies can be used as indicative parameters of internal damages. Modal analysis may be used to quantify internal defects through shifts in the natural frequencies of a structure [23, 27–29]. *NNs* simulations can accurately and robustly respond to dynamic characteristics of *LCM* structures and they can be used to predict the damages of *LCMs*. The *NN* uses natural frequencies as input and the corresponding damage information (location, size, and shape) as an output to the network [30–33].

Smart instrumentation has been extensively tested to specify damage in *LCMs* using permanent sensors as monitoring or field evaluation systems. Fiber optic sensors are attractive candidates for smart composite applications. They may also be incorporated into a composite element since their temperature tolerances and small sizes are compatible with composite processing and structure. Optical sensor data is commonly processed with *NNs* [34]. Watkin *et al.* [35] used *BP NN* and fiber optic vibration sensors to predict different sizes and locations of delaminations in composite beams. The fiber optic sensors measured the first five modal frequencies for healthy (undelaminated) and delaminated cantilever beams made of eight-ply glass/epoxy composite laminates. The delamination size and location prediction resulting from the network simulation had an average error of *5.9%* and *4.7%* respectively. Table 1 shows the experimental sizes, the predicted sizes, and the percentage differences between them. The results might be improved by using training data from more accurate analysis. Further studies are needed so as to obtain an efficient health monitoring capability in composite structures with integral fiber optic sensors and *NN*. The fiber optic outputs may also be fed directly into a *NN* to provide accurate information for complex structures.

Table 1: A comparison between true and predicted delamination sizes by using *NN* [35].

True Sizes (*cm*)	*NN* Sizes (*cm*)	Differences (%)
1.27	1.29	1.2
2.54	2.81	10.6
3.81	4.22	10.7
5.08	5.40	6.3
6.35	6.41	0.9

Chakraborty [3] introduces an approach that predicts the presence of embedded delamination (in terms of location, shape, and size) in fiber reinforced plastic composite laminates by using *BP NN* with 3 layers (input, hidden, and output). The network has been tested to predict the presence of delamination along with its size, shape, and location. It has been observed that the network can learn effectively the size, shape, and location of a delamination embedded in the laminate and can predict reasonably well when tested with unknown data set. Simulated data has been used for training and testing the network, but the approach has not been tested by using real life data sets so as to specify its actual efficiency.

Crispin and Gerard [36] proposed an approach that combines a simple but sensitive optical fiber vibration sensor, a fast Fourier transformation (*FFT*) pre-processing stage, and *BP* multi-layer perceptron *NNs* to detect damage in carbon-fiber reinforced polymers (*CFRP*). In this study two *NNs* were used, which were receiving data from four sensors fixed in the composite plates and using these information to specify the location of the damages on the plates. One network was responsible for specifying the location of the damages from the *FFTs* of strain and the second one for finding their magnitudes. The system detected the damages with an average error of *7.08%*, when data sets with simulated damages were used. In the later work, the composite panel is fitted with a number of ribs and stringers to simulate a real load-bearing *CFRP* skin structure. This made the task of loading impacts harder but a *92%* success was achieved. The system was trained successfully to differentiate between test transient signals from *CRFP* plates with four levels of damages and with three degrees of simulated impact damage.

3.2 Electrical Conductivity

The implementation of natural frequencies as indicative parameters for failure detection in *LCMs* by using *NN* has already been articulated. But sometimes it may happen that the measurement of the frequencies is very difficult due to some limitations in hardware and connectivity associated with the sensors (e.g. space and bandwidth restrictions). Another approach to identify delaminations in *LCMs* is by embedding fiber-optic strains into them, so as to measure the strain distribution [38, 39]. Unfortunately, this may reduce the static and fatigue strengths, and increase the total weight of the material. In addition, the optical fiber sensors and the sensing systems are very expensive. These guide to another form of smart technology to identify failures in *LCMs*.

Some of the materials used in the *LCMs* are electrical conductors, e. g. carbon and graphite fibers. Therefore, the measurement of the electrical resistance appears to be a valuable technique for the detection of different types of failures in *CFRP* laminates, which does not cause reduction of static strength or fatigue strength. Moreover, the electric-potential method does not cause increase in weight. This method has been adopted by many researchers, e.g. Irving and Thiagarajan [40], and Abry *et al.* [41]. In the case of *CFRP*, the carbon fibers are not only used as a reinforcement material, but also as sensors of damage detection and predictions [42]. Dae-Cheol and Jung-Ju [42] have investigated this kind of damage detection by mounting electrodes on the surface of the *CFRP* structures. They have showed that the measured stiffness change have a similar trend as the electrical resistance change during fatigue tests. The electrical resistance has showed gradual increase while the stiffness was decreasing and showed an unexpected change when the final fatigue stiffness changed suddenly. They have used *NN* to investigate the relation between the electrical resistance damage parameter, fatigue life, and stiffness reduction, which showed good relationship (Figure 2).

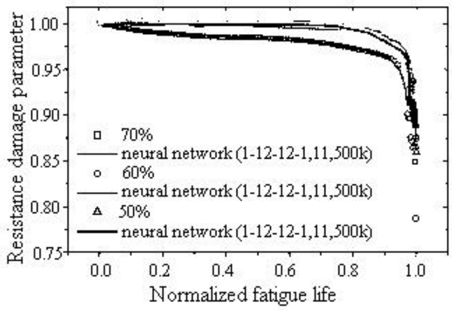

Figure 2: Comparison of fatigue life and resistance damage parameter predicted by neural network and experimental results [42].

Figure 2 shows the relationship between electrical resistance and fatigue life using an *NN*. The input node of the neural network is the electrical resistance damage parameter and the output node is fatigue life of stiffness reduction. Three stress levels, 70$\%$, 60$\%$, and 50$\%$ of the average static ultimate strength were selected. The error convergence of the network relies on the structure of the hidden layer. In this case, it shows better results with two hidden layers than with one hidden layer. About 11 to 18 number of experimental data were used as learning input data. After the learning step, a graph very similar to the experimental results were acquired. Thus, it is possible to predict specimen damage by monitoring electrical resistance using a neural network.

Graphite fibers in graphite/expoxy laminated composite are also very good electric conductors and the epoxy matrix is an insulator. Generally, electric conductivity is very high in the direction of the fibers and much lower in the transverse direction of the fibers or may vanish under normal conditions [43]. When a delamination grows between plies in a graphite/expoxy composite, the electrical resistance increases in the composite. Therefore, delaminations can be detected by calculating the variation of electric resistance in this kind of composites. Todoroki and *et al.* [44–47] have shown that electrical resistance change method using response surfaces is very effective in identifying delaminations in laminated composite materials both experimentally and analytically.

They have proposed a schematic representation of a delamination monitoring system (Figure 3).

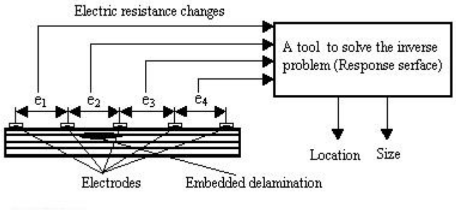

Figure 3: Schematic representation of delamination identification method using electric resistance change method with response surfaces [44].

In Figure 3, multiple electrodes are mounted on the surface of a specimen with equal spaces from each other. All of these electrodes are placed on a single side of a specimen. Usually it is impossible to place electrodes and lead wires outside of the aircraft structures. Mounting of electrodes on the singe side surface represents modeling of electrode attachment in thin aircraft shell type structures. Electrical resistance change of each segment between electrodes is measured for various cases of location and size of delaminations. Using the measured data, the relationships between electrical resistance changes and delaminations (location and length) are obtained using the response surfaces. The main draw back identified for this method is the high number of experiments that must be performed to obtain sufficient number of sets of electrical resistance changes. The response surface is similar to *NNs* and it is a widely adopted tool for quality engineering fields. Response surface methodology comprises regression curve fitting to obtain approximate responses, design of experiments to obtain minimum variances of responses, and optimizations using approximated responses [46, 47].

3.3 Lamb Waves

Lamb wave (*LW*) was first introduced by Sir Horace Lamb in *1917* [48]. *LW* is one of the widely used techniques in *NDE* for failure detection and prediction in *LCMs*. *LWs* are acoustic waves that can be launched into relatively thin solid plate with free parallel surfaces and are also known as plate waves [49]. There are different kinds of techniques used to propagate and receive *LWs*. These techniques have been implemented in a variety of configurations, including the use of single purpose devices (e.g. transducers) that use separate actuators (sources or transmitters) and sensors (receivers) to propagate and monitor the propagated waves and/or reflected waves individually, and multipurpose transducers in which, a single transducer is used to actuate and sense the waves simultaneously. The simplest methods of the multipurpose transducers use piezoelectric transducers, which can be used as transmitters or sensors. The single purpose transducers are like laser transmitters and optical fiber sensors. Each of these techniques has its own unique properties and different analytical complexity in detecting and predicting specific types of failures in these materials. The *LWs* generated by a transmitter propagate through the material and reflected by the failures and the surfaces of the material back to the sensors. The signals reflected to the sensors contain some information (e.g. size, location, and orientation) about the failures and they can be used to test the structural integrity of the material. *LWs* excite the whole volume of the structure along the line between the transmitter and receiver. They can propagate over long distances. However, their dispersive nature and the existence of many modes simultaneously can complicate the interpretation of the acquired signal [49].

The first implementation of *LWs* for damage detection was introduced by Worlton in *1960* [50]. He investigated the dispersion curves of aluminum and zirconium to describe analytically the characteristics of the various modes that would pertain to nondestructive testing applications. During the late *1980* and *1990*s, work began on the application of *LW* to composite materials [4].

Many researchers have adopted the *LWs* together with *NNs* as a technique for failure detection and prediction in *LCMs*. Su and Ye [51] have demonstrated a *LW* propagation-based quantitative identification scheme for delamination in *CFRP* composite structures by using a multi-layer *BP NN*. An Intelligent signal processing and pattern recognition package was developed to perform the identification, where a *BP* was trained using spectrographic characteristics extracted from acquired *LW* signals. Excellent quantitative diagnosis results for damage parameters in terms of presence, location, geometry, and orientation were achieved. Although a certain amount of time is inevitably spent on the preliminary off-line development of the *NN*, the researchers have not tested the developed *NN* and the structural health monitoring system to diagnose an actual failure performed instantly online.

Yuan and Wang [4] have introduced a damage signature based on wide-band *LW* for on-line delamination and impact detection monitoring system applied to honeycomb sandwich and *CFRP* structures. The damage signature has been introduced together with a Kohonen *NN* to determine the presence and extent of damage in the composites, while diminishing the influence of different distances between the transmitters and sensors. They have showed the efficiency and the reliability of the proposed method for the different types of the materials used, which suffer various levels of damage.

4 Conclusions

Combined computational techniques with Neural network as a quantitative method and natural frequencies, electrical conductivity, and lamb waves as non-destructive methods have been extensively used to identify failures in laminated composite materials. Neural networks have demonstrated robust and uncontroversial capabilities for complex failure detection and prediction in laminated composite materials with small errors. These failures include delamination, matrix cracking, fiber fracture, and debonding in terms of size, location, and shape.

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