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# NEURAL NETWORKS AND EVOLUTIONARY OPTIMIZATION TECHNIQUES AND THEIR APPLICATIONS IN FATIGUE LIFE ASSESSMENT OF COMPOSITE MATERIALS-A BRIEF REVIEW

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*Abstract* – Modeling of fatigue life of composite materials under various loading and environment conditions becomes important and challenging task from viewpoint of performance and reliability as it forms a basis for lifetime assessment of composite structures under complex variable state of stress. Application of soft computing techniques as new approach and route for modelling of composite material fatigue lives has attracted a great interest recently. The applications of soft computing techniques in fatigue life assessment of composite materials are reviewed and discussed in this paper.

*Keywords*: Neural networks; evolutionary algorithms; optimization; fatigue life assessment; composite materials.

## 1. Introduction

Driven with advancement of technology applications, requirements for new classes of materials having desired properties, meeting special engineering applications, cost-effective and also long lasting are continuously increasing in the last decades. Introducing new materials in line of applications, while offering favourable and potential benefits, it clearly also brings many challenges. For an instance, the new materials characterization to fully understand their characteristics and performance needs to be carried out intensively. Moreover, new parameters of material behaviour may need to be introduced, implemented and tested in development of such materials from design to production stages, while further process optimization may be necessary as well. Modelling and characterization of such new materials under various loading and environment conditions hence become important tasks to provide valuable and useful design information thoroughly.

From viewpoint of performance and reliability, it is always crucial to understand the fatigue degradation of materials in various applications to ensuring the long-term reliability of a component or structure. It is well known that fatigue failure is the most important aspect in design of structures because it is closely related to performance, durability and reliability of the structures (Reifsnider, 1991). It is reported from extensive study by the US National Institute of Standards and Technology that the majority of structural failures occur through a fatigue mechanism and the fatigue failures can count approximately 60% of the examined failures (Manson and Halford, 2006). Lifetime assessment of materials to assess their useful lifetime during their service in design thus becomes a challenging task. The ability to make accurate predictions of fatigue durability is also critical to the design optimization (Post *et al*., 2008; Schijve, 2009).

Recently, composite materials have represented important classes of developed materials for various structural and industrial applications, ranging from transportation and construction to oil and gas and aerospace industries. Composite materials such as fibre reinforced polymer (FRP) composites have become more popular materials instead of metals in many components of automotive, aircraft, ship hull and wind turbine blade structures due to their excellent properties such as high strength to weight ratio, tailored properties along preferred direction and high corrosion resistance. Applied in many important as well as critical applications, it is therefore desirable that behaviour and responses of composite materials under spectrum or variable amplitude fatigue loadings can be comprehended and assessed accurately.

Nonetheless, in contrast to that of metals, modelling of fatigue life of composite materials under complex and spectrum loading conditions comes with a greater challenge and complexity as many factors or considerations must be taken into account in the modeling of fatigue life of composite materials, such as fibre and matrix types, lay-ups or laminates, fatigue states governed by stress ratios-R and on-axis/off-axis orientations, anticipated failure modes as well as related influence of manufacturing method chosen. As a result, the modelling of fatigue life of composite materials becomes complicated and developing a universal understanding of the performance of composite materials under spectrum fatigue loadings is also very difficult as many factors should be included and anticipated in the model (Reifsnider, 1991; Harris, 2003; Vassilopoulos, 2010; Passipoularidis, 2011).

Ideal approach for modelling of fatigue life of composite materials, as described by Sendeckyj (1991), is the one which is based on a damage metric that can accurately model the experimentally observed damage accumulation process, take into account all related material, test and environmental variables, correlate the data for a large class of materials, permit the accurate prediction of laminate fatigue behaviour from lamina fatigue data, be extendable to two-stage and spectrum fatigue loading as well as take into account fatigue data scatter. However, as so many factors should be included in the model as mentioned previously it is obvious that such an approach which can meet all these requirements simultaneously is very difficult to be developed. In addition, not only the complexity of the model itself, but also the experimental works required to extract the appropriate material parameters of the model would hinder such model development as the amount of experimental data is strongly dictated by the number of model parameters (Hour and Sehitoglu, 1993). Thus, such model development will be frequently impeded by a large amount of fatigue testing data needed, which is very costly and time consuming to collect. In fact, in most cases researchers only had limited experimental fatigue data in hands.

Keeping the above matter in mind, several approaches have been proposed for the modelling of fatigue life of composite materials with the main aim to provide prediction of fatigue life of composite materials under variable amplitude loading by utilizing less fatigue data but at the same time ensuring reasonably accurate fatigue life prediction. Here, the ‘prediction’ term should be meant in term extrapolation i.e. the model capability should be examined for new loading conditions for the same material or it is examined for other material systems based on model derived or developed for a specific material.

In general, the approaches for modelling of fatigue life of composite materials may be further classified into two categories (Sendeckyj, 1991): fatigue damage accumulation and macroscopic failure (empirical) theories. In the first approach, a damage metric such as residual strength, residual stiffness, crack length, delamination area will be introduced and used as a damage accumulation indicator for a composite during fatigue loading and it will be further correlated to the composite fatigue life through a well determined criterion. On the other hand, the later approach does not take into account the damage accumulation and mechanisms occurring during fatigue loading. Rather, a simpler idea is adopted in the second approach i.e. applied cyclic stress (S) or strain ($\varepsilon$) is directly associated with operational lifetime or fatigue cycles (N) that a material can withstand or endure under the applied stress or strain via the S-N or $\varepsilon$ -N curves. Clearly, the aforementioned approaches in predicting fatigue life of composite materials represent two main concepts in the fatigue life prediction: the damage tolerant and safe-life concepts i.e. whether the presence of damage is allowed as long as it is not critical and leads to sudden failure, or on the other hand the structure is only allowed to operate until a certain value of operational lifetime before the initiation of any measurable damage or cracks (Vassilopoulos, 2010).

Considering that fatigue is essentially a stochastic process in nature, a new approach or paradigm has been proposed and introduced recently in predicting the fatigue life of composite materials by using and exploiting soft computing or computational intelligence techniques. Different with the aforementioned approaches, the soft computing-based fatigue life prediction approach has capability to take into account and cope with the stochastic and uncertainty aspects which are well known inherent with the fatigue phenomena. Inspired by biological or nature processes, the soft computing models mimic and emulate certain characteristics in the nature processes to perform a kind of optimization search and task. Thus, the soft computing models have ability to extract and represent nonlinear interactions among variables involved in the fatigue process. In fact, fatigue life prediction of composite materials is the field where computational intelligence or soft computing techniques found to be successful and useful tools which are able to produce reliable prediction using a limited body of fatigue data and in turn supporting design decisions very soon and reliably. In addition, it is also interesting to note that the soft computing approach is also able to provide bounds of fatigue life prediction, thus providing statistical representative of fatigue lives and describing the scatter of fatigue lives. As a result, the approach attracted great interest in fatigue research community and has been a new route in the task of fatigue life prediction of composite materials in recent years.

In this paper, a brief review of neural networks and evolutionary optimization techniques and their applications in the field of fatigue life assessment of composite materials is presented and discussed. It is shown that several models of soft computing techniques have been developed and actively employed in recent years for the fatigue life assessment of composite materials. In the first section of this work, fatigue life assessment of composite materials in wide range of applications from unidirectional to multidirectional laminate are highlighted. It is shown that soft computing techniques particularly neural networks and evolutionary algorithms have been proven to be sufficient and useful tools for such modelling task.

## 2. Neural Networks and Evolutionary Algorithms for Optimization

Neural networks (NN) are inspired by the biological network of neurons in the human brain that learns from external experience, handles imprecise information, stores the essential characteristics of the external input and generalizes previous experience (Eeckman, 1992).

In the biological neural networks, a neuron has three main components: dendrites (receiver), soma (cell body) and axon (transmitter). Further, the axon eventually branches into strands and sub-strands and at the terminals of these strands are synapses. A synapse acts as an elementary structure and functional unit connecting two neurons, that is an axon strand of one neuron is connected to a dendrite of another neuron by the synapse. The processing of information is as follows: when the input signals (electrical impulses) reach the synapses, certain chemicals called neurotransmitters are released. The neurotransmitters then diffuse across the synaptic gap (junction). The receivers (dendrites) receive the signals. The incoming information is summed up by soma and then delivered along the neuron's axon to the dendrites at its end. The information will again be passed if the stimulation caused by the signals has exceeded a certain threshold. Otherwise, it would not be passed further. The synapse's effectiveness is adjusted by the signals passing through it so that the synapses can learn from the activities they involve and participate. Fig. 1 depicts the schematic of a neuron in biological networks.

NN attempts to mimic the biological neural networks: the processing unit is the artificial neuron or node. The synapses or inter-neuron connections are described by synaptic weights. An operator performs a summation of the input signals (NN inputs) weighted by the respective synapses. Finally, an activation function transfers the summation and also confines the permissible amplitude range of the output signals. Hence, NN are essentially devices of parallel and distributed processing of many interconnected neurones (nodes or hidden units) whose associated weights determine the strength of the signal passed through them, which simulate the basic operating principles of the neurones in biological brain. As no particular structure or parametric form is assumed a priori and the strengths of the connections are computed in a way that captures the essential features in the data, NN has abilities in modeling complex nonlinear processes without a priori assumptions about the nature of the generating process by learning and generalizing inputted patterns of the process to be sought (Rumelhart *et al*., 1986). Therefore, NN is suitable for nonparametric statistical inference either in regression or classification tasks.

The most widely used procedure in NN learning is backpropagation, which is a breakthrough in the resurgence of interest in NN study (Rumelhart *et al*., 1986). The term backpropagation refers to the manner in which error information from output layer is backpropagated through the layers within the network. The process is repeated consecutively immediately after the input samples are propagated forward through the network. For each propagating-backpropagating pass, the weights of the network are updated iteratively. The updating process is repeated until predefined stopping criterion is met. The stopping criteria could be in form of performance goal measured by mean square error (MSE), maximum iteration number, minimum performance gradient and minimum change in performance. During the backpropagation procedure, NN learning task is hence in principle a minimization problem to particular objective function and the minimization problem is related to the method for updating the NN weights (Nabney, 2002; MacKay, D.J.C., 2004). A basic method for updating NN weights is gradient descent, while other optimization methods such as Levenberg-Marquardt and conjugate gradient methods for updating the NN weights are also available in literature (Fletcher, 1980; Nocedal and Wright, 2006; Foresee and Hagan, 1997). It is worth noting that Funahashi (1989), Hartman *et al*. (1990) and Hornik *et al*. (1989) have proved that a single hidden layer is sufficient for the NN to approximate any function to any random degree of accuracy, with the condition that the activation functions of the network are nonlinear, which is known as the universal approximation theorem.

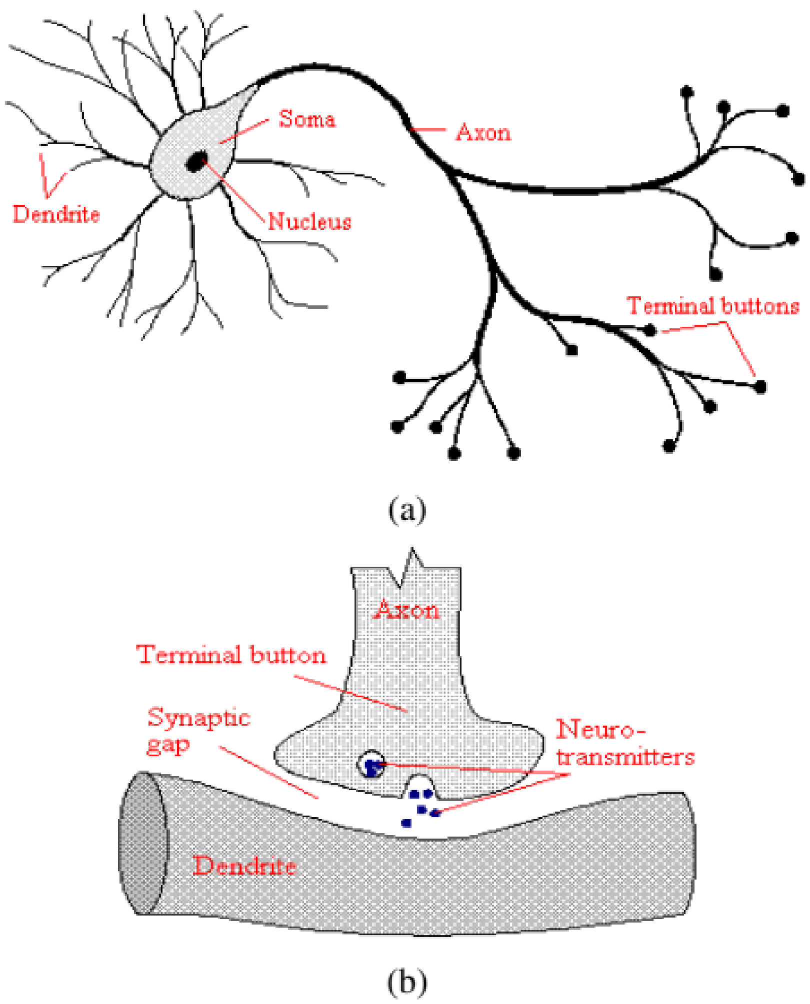


**Fig. 1**. A schematic of (a) biological neuron, and (b) synapse (Fraser, 1998).

On the other hand, evolutionary computation or algorithm (EA) is an area of computer science that uses ideas from biological evolution to solve computational problems (Mitchell and Taylor, 1999). Based on population-based collective learning process, classes of evolutionary algorithms such as genetic algorithms (Holland, 1975), evolution strategies (Rechenberg, 1973), evolutionary programming (Fogel, Owens and Walsh, 1996) and genetic programming (Koza, 1992) share a common conceptual base of simulating the evolution of population individual via the processes of selection, mutation and reproduction.

The general procedure of EA may be described as follows (Grosan and Abraham, 2007):

a. A population of candidate solutions for the optimization task to be solved is initialized.
b. New solutions are created by applying reproduction operators (mutation and crossover).
c. The fitness of solutions is evaluated and suitable selection strategy is then applied to determine which solutions are to be maintained into the next generation.
d. The procedure is iterated until stop criteria (such as: performance goal, maximum iteration number, minimum change in performance, time) are met.

It can be seen that the behaviour of EA is determined by exploitation and exploration relationship kept throughout the run by which prior knowledge and heuristics of the individuals in population are incorporated and evolved through the processes which continue to adapt in a changing environment (Subudhi and Jena, 2011).

Bearing simplicity, self-adaptation and robust response to changing circumstance, EA is suitable for many difficult optimization problems in particular multi-modal, multi-objectives, mixed variables and noncontinuity problems. In addition, the use of EA for solving optimization problems does not dictate special conditions or properties for the objective function to be used, which is another advantage of using EA for solving optimization problems.

In fact, one can clearly see that NN represents a paradigm of programming which relies on massivity and distribution of processors, while EA represents another paradigm of programming which relies on the concept of adaptation and selection through interaction. Both approaches are therefore creature and nature inspired algorithms which are beneficial for solving several problems and applications of optimization (Mohamed *et al*., 2012).

## 3. Neural Networks and Evolutionary Algorithms for Fatigue Life Prediction of Composite Materials

The characteristic of NN that can be taught to emulate relationships in sets of data to subsequently predict the outcome of another new set of input data, for example, another composite system or a different stress environment, is exploited to yield faster acquisition of fatigue data, thus reducing experimentation time and cutting down the associated high costs. In addition, the use of EA in the field of fatigue life prediction has also opened a new horizon and perspective as genetic programming as a class of EA has been proved as a stochastic non-linear regression analysis tool in modeling the fatigue life of several composite materials which compares favourably with other conventional methods such as linear regression and Weibull statistics that are commonly used for this type of material analysis (Vassilopoulos *et al*., 2008).

In metals applications and analyses, NN have been previously employed for elevated temperature creep-fatigue life prediction (Venkatesh and Rack, 1999), fracture toughness and tensile strength of microalloy steel evaluation (Haque and Sudhakar, 2002), prediction of fatigue crack growth rate in welded tubular joints (Fathi and Aghakouchak, 2007), while genetic algorithm (GA) has been employed as parameterization tool for fatigue crack growth of Al-5052 (Bukkapatnam and Sadananda, 2005) as well as optimization tool for fuzzy logic and NN models in life prediction of boiler tubes (Majidian and Saidi, 2007). NN has been also employed to build a probability distribution function for fatigue life prediction of steel under step-stress conditions (Pujol and Pinto, 2011). Also, Klemenc and Fajdiga (2012) have employed a class of evolutionary algorithms to estimate S-N curves and their scatter using a differential ant-stigmergy algorithm (DASA). In (Klemenc and Fajdiga, 2013), the authors have extended the use of evolutionary algorithms of GA and DASA for estimating E-N curves and their scatter.

In recent years, soft computing techniques have found their applications in the field of fatigue life assessment of composite materials in particular under variable amplitude loading conditions (Aymerich and Serra, 1998; Lee and Almond, 2003). The use of soft computing techniques in fatigue life assessment of composite materials has a wide range of applications from unidirectional (Al-Assaf and El-Kadi, 2001; El-Kadi and AlAssaf, 2002) to multidirectional laminate (Freire Junior *et al*., 2005; Vassilopoulos *et al*., 2007; Vassilopoulos *et al*., 2008; Freire Junior et al., 2007; Freire Junior *et al*., 2009). Moreover, soft computing techniques have been also proven to be a sufficient tool for modelling fatigue life of composite materials under uniaxial to multiaxial state of stress. The comprehensive review of the recent works is presented here.

Al-Assaf and El-Kadi (2001) and El-Kadi and Al-Assaf (2002) assessed the fatigue life of unidirectional glass fiber/epoxy laminae using different neural network paradigms, namely feed forward (FF), modular (MN), radial basis function (RBF) and principal component analysis (PCA) networks, and compared the prediction results to the experimental data. Specimens with five fiber angle orientations of 0°, 19°, 45°, 71° and 90° were tested under three stress ratio-R conditions of -1, 0 and 0.5. Ninety two experiment data made up the application data for the networks. They found that NN can be trained to model the nonlinear behaviour of composite laminate subjected to cyclic loading and the prediction results were comparable to other current fatigue-life prediction methods.

Freire Junior *et al*. (2005) followed different approach, by which NN was utilized to build constant life diagrams (CLD) of fatigue. The researchers built CLD of a plastic reinforced with fiberglass (DD16 material) with $[90/0/\pm45/0]_S$ lay-up. Four training data sets (each set consists of 3R, 4R, 5R and 6R values, respectively) were set up from twelve stress ratio-R values. It was found that the use of NN to build CLD was very promising where the NN model trained using only three S-N curves could generalize and construct other remaining S-N curves of the CLD building. For better generalization, however, six S-N curves should be utilized in NN training. Vassilopoulos *et al*. (2007) criticized that the determination of six S-N curves was a costly task for the NN prediction purpose. Instead, these authors used a small portion, namely 40 – 50%, of the experimental data. It was shown that it is possible to build CLD using the small portion data and NN was proven to be a sufficient tool for modelling fatigue life of GFRP multidirectional laminates. In their further work, Vassilopoulos *et al*. (2008) have employed genetic programming for modeling the fatigue life of several fibre–reinforced composite material systems. It was shown that if the genetic programming tool is adequately trained, it can produce theoretical predictions that compare favourably with corresponding predictions by other, conventional methods for the interpretation of fatigue data. It was also pointed out that the modeling accuracy of this computational technique was very high. In addition, the proposed modeling technique presented certain advantages compared to conventional methods. The new technique was a stochastic process that led straight to a multi-slope S–N curve that follows the trend of the experimental data, without the need for any assumptions.

Bezazi *et al*. (2007) have investigated fatigue life prediction of sandwich composite materials under flexural tests using a Bayesian trained artificial neural network. The authors noticed the good generalization of NN trained with Bayesian technique in comparison to that with maximum likelihood approach in predicting fatigue behaviour of the sandwich structure. Nonetheless, only one lay-up configuration was considered in the work.

Freire Junior *et al*. (2007, 2009), in their next attempts, showed that the use of modular networks (MN) gives more satisfactory results than feed-forward (FF) neural network. However, it was still necessary to increase the training sets for better results. Bucar *et al*. (2007) presented an improved neural computing method for describing the scatter of S–N curves.

The works showed that soft computing techniques have been proven to be a sufficient tool for modelling fatigue life of composite materials, ranging from unidirectional to multidirectional laminate types and from uniaxial to multiaxial state of stress under multivariable amplitude loadings. Furthermore, with the introduction of EA and the combined system identification technique and NN, perspectives on fatigue life prediction of composite materials based on soft computing framework have been broaden. Moreover, it is also possible to combine both NN and EA techniques to be used in predicting the fatigue life of composite materials so that the effectiveness of the fatigue life prediction task can be further enhanced. In fact, it is still necessary to optimize the task of fatigue life prediction of composite materials under variable amplitude loading and/or multiaxial state of stress for much more efficient fatigue life assessment of composite materials in particular by utilizing less fatigue data but at the same time ensuring reasonably accurate prediction. As stated by Zhang and Friedrich (2003) that fatigue behaviour is still so complicated that the problem requires more effort before NN can be used with more confidence. Therefore, further developments and implementations of other optimization techniques for fatigue life assessment of composite materials would be interesting as research subjects in future.

## 4. Conclusions

In the present paper, a brief review of applications of NN and EA optimization techniques in fatigue life assessment of composite materials has been presented. Main motivation for using such techniques is to produce efficient fatigue life prediction of composite materials by cutting down the fatigue tests and cost, but at the same time ensuring reasonably accurate fatigue life prediction. Inspired by the biological network of neurons in the human brain that learns from external experience, handles imprecise information, stores the essential characteristics of the external input and generalizes previous experience, the optimization techniques have been shown as promising techniques for modelling fatigue life of composite materials, ranging from unidirectional to multidirectional laminate types. Further developments and implementations of other optimization techniques for fatigue life assessment of composite materials would be interesting as research subjects in future.

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