CHAPTER 1

INTRODUCTION

Neural Networks (NN) found its application in fatigue field, especially in fatigue life assessment of composite materials. The use of NN promises faster acquisition of fatigue data for a new material and/or a new loading condition, reducing experimentation time and thus cutting down the associated high costs. This is due to the NN advantages of convenient data handling, ease of implementation as well as wide availability of software environments to implement it. In this chapter, relevant background, motivation and importance of this study are described.

1.1 Background

In designing structures, including those of composite materials, fatigue failure becomes most concerned aspect, because it is closely related to performance, reliability and durability of the structures. A fundamental question of "How long will this component last" need an answer that must be established from a rational approach under fairly general circumstances [1]. As a consequence, lifetime assessment of a component material becomes an important part in design phase to assess its useful life.

The need for lifetime assessment of composite materials is also driven by the needs to speed up the time frame from the research stage to the market place and also influenced by the intensive use of composite materials that require performance evaluation in the increasingly competitive market.

From the above needs, specifically from a design engineer's point of view, fatigue life assessment for multivariable amplitude loading is the most challenging, because in fact a real structure or component is exposed to an extremely complicated pattern of stress cycles of varying amplitude and mean stress along its service life. This means in fatigue life assessment of multivariable amplitude loading, a wide spectrum of varying amplitude and mean stresses of loading need to be considered.

If covering such a wide spectrum of varying amplitude and mean stresses of loading in the fatigue life assessment is most concerned, performing fatigue testing at several different stress ratios (R) should be done, although it would be very time consuming and costly. In fact, fatigue life assessment of a material is frequently faced with tight compromises between the available time, effort, and cost and the condition more prominent for multivariable amplitude loading. On the other hand, fatigue strength data at several stress ratios are not always available.

In the context of predictive modeling, Artificial Neural Networks (ANN) offer a reliable fatigue life assessment which is capable of examining fatigue life efficiently without impairing predictive accuracy [2, 3].

ANN, commonly just called as NN, is a subclass of Artificial Intelligence (AI). Among others, two definitions of AI from Tanimoto [4] and Bonnet [5] are cited, respectively: "the study that encompasses computational techniques for tasks that apparently require intelligence when performed by humans" and, "the discipline that aims to understand the nature of human intelligence through the construction of computer programs that imitate intelligent behavior". Some elements of knowledge base, search techniques and logical reasoning are usually involved in AI. Besides NN, fuzzy logic, genetic algorithms, support vector machines and probabilistic reasoning are in the same category of Artificial Intelligence or also known as *soft computing*.

1.1.1 Historical Background of NN

NN is 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 [6].

In the biological neural networks as depicted in Figure 1-1, 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 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. It can be said that the synapse's effectiveness can be adjusted by the signals passing through it that the synapses can *learn* from the activities they involve and participate.

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.
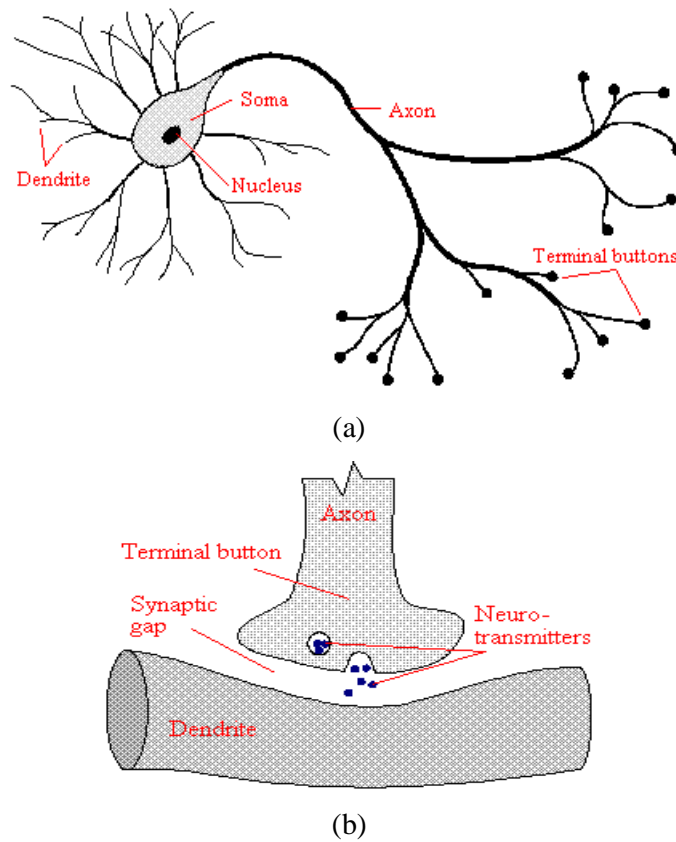

(a)

(b)

Figure 1-1 A schematic drawing of (a) a biological neuron, and (b) a synapse [7].

NN model dated back to pioneering work of McCulloch and Pitts in 1943 [6]. They proposed a binary threshold unit as a computational model for an artificial neuron (node). The mathematical neuron computes a weighted sum of its n input signals x_j, where $j = 1, 2, \ldots, n$. It generates an output of 1 if the sum is above a certain threshold u. Otherwise, an output of 0 results. This characteristic is as mentioned in the previous section that the specific transmitter substances released from the sending side of the junction have the effect to raise or lower the electrical potential inside the body of the receiving cell. The neuron fires, if the potential reaches a threshold.

Mathematically, the model can be stated as:

$$y=f\left(\sum_{j=1}^{n} w_j x_j - u\right) \tag{1-1}$$

where $f(\cdot)$ is a unit step function at 0 and w_j is the synapse weight associated with the jth input. In addition, u is often considered as another weight $w_0 = -u$ (it will now be referred to as bias b) attached to the neuron with a constant input $x_0 = 1$.

The single neuron model and the unit step function are represented in Figure 1-2.

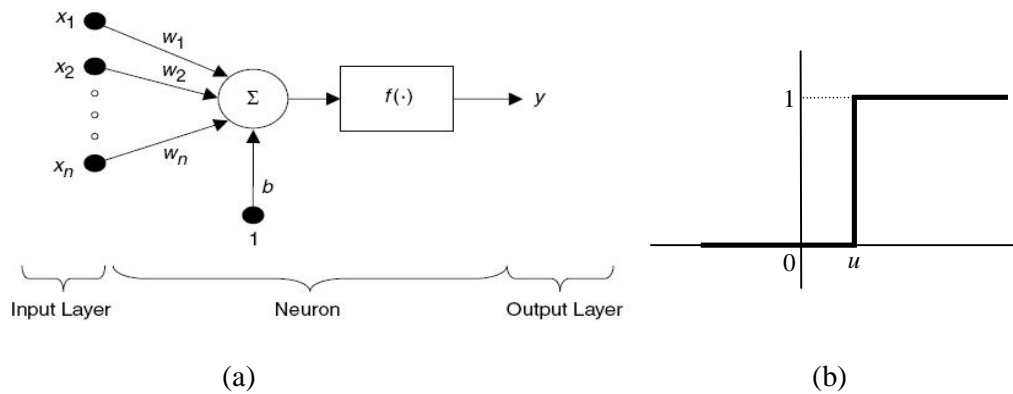(a)   (b)

Figure 1-2 (a) McCulloch and Pitts' neuron model, and (b) unit step function.

Even though the McCulloch and Pitts model provides crude analogy to a biological neuron, a synchronous arrangement of such neurons with appropriately chosen weights could principally perform universal computations. The model can also be expanded to general multi-layer perceptron (MLP) with other kinds of activation function.

The next influential development in NN was the first practical application of NN in pattern recognition problem. In 1958, Frank Rosenblatt invented a class of neural networks called the *perceptron* network and he also developed a learning procedure for training the network (determining the weights and threshold), given a set of training patterns or examples, to solve the pattern recognition problem [8]. It had been proven that the perceptron learning procedure will always converge to the correct network weights after a finite number of iterations (called as *the perceptron convergence theorem*). The Rosenblatt's approach was a novel method which is now called as supervised learning.

Unfortunately, pattern recognition problems that can be handled by the perceptron network are the ones whose training patterns belong to two linearly separable classes, as stated by Mavin Minsky and Seymour Papert [8]. In real situations, whether the patterns are linearly separable are unknown. Minsky and Papert raised the skepticism in the ability of multi-layer perceptron network to overcome the limitation. As a result, the enthusiasm of researchers in the ANN field had declined for almost 20 years.

In 1980's, the answer to the skepticism was found The answer was related to *the backpropagation algorithm* rediscovered and popularized by Rumelhart et al. in 1986 [9]. The credit for the backpropagation algorithm was given to Rumelhart et al. because the researchers proposed its use for machine learning and demonstrated how it could work. Rumelhart work forced the popularity of the algorithm for the training of multi-layer perceptron and marked the resurgence of interest in NN field. Now, the backpropagation algorithm is the most widely used algorithm in NN learning.

1.1.2 NN Capabilities

The robustness of NN as a computational tool is now well-known due its learning ability, covering from pattern recognition, data classification, extracting to storing information capabilities. Moreover, it has generalization ability in contextual information processing and also various training algorithms corresponding to different NN architectures (see subsection of 3.1 for NN architecture). Therefore, NN offers a means of handling many multi-variance parameters for which the relationships or interactions among them are difficult to be established due to their complexity and non-

linearity. In addition, NN can respond to new inputs or environments that have never been seen before and then predict the associated outputs and making it suitable for prediction and control tasks. Finally, when appropriately trained, NN is efficient and robust, meaning that it is possible to achieve a good accuracy with appropriate training algorithm and structure.

1.2   Defining a Limited Set of Stress Ratios

In this study, the author further defines a set of stress ratios consisting of only two stress ratios as a limited set of stress ratios. The importance of this definition is to differentiate between this research study and the previous studies in NN modeling for fatigue life prediction. As mentioned before, previous researchers utilized fatigue data from at least three stress ratios-R as training set in their NN modeling to obtain comparable and reasonable fatigue life prediction results. No efforts have been made, so far, to utilize less training data set, but at the same time ensure reasonable fatigue life prediction results.

Further, a limited set of stress ratios could be categorized as well-distributed and not well distributed in constant life diagrams (CLD) regions. A set of stress ratios is said to be well-distributed in CLD regions if the stress ratios are symmetrical in position to one another. Otherwise, it is said as not well-distributed. For instance, a set of stress ratios of 0.1 and 10 or 0.5 and 2 is said to be well-distributed in the CLD region because the pair of the stress ratios are symmetrical in position to one another. On the other hand, a set of stress ratios of 0.1 and 0.5 is said to be not well-distributed. CLD is discussed thoroughly in Chapter 2.

Thus, the extrapolation capability of NN or the NN capability to predict fatigue lives with limited set of stress ratios whether well-distributed or not is to be further examined. This is to be fulfilled through this study in fatigue life prediction of composite materials, especially for polymer matrix composites.

This study presents a Neural Networks (NN) modeling to predict the fatigue lives of polymeric-based composites under variable amplitude loading with limited set of stress ratios. The rational for the current study is that previous related studies offer less

satisfactory prediction results to this kind of fatigue problem in the sense that less generalization capability of the previous NN models and more training sets needed for better predictions. The study is in the spirit of how a limited body of fatigue data could be optimized by using an NN model and provides fast and accurate support for design decisions. The proficiency of the NN models for fatigue life prediction under variable amplitude loading was validated to experimental data.

1.3 Problem Statement

Fatigue life prediction of composite materials ranging from unidirectional lamina to multidirectional laminate using NN have shown promising results. Nevertheless, in the condition of variable amplitude loading, further investigations are needed due to two key problems. Firstly, more fatigue data is required for training set of the NN model. This is in contrast to the fact that fatigue testing is costly and time consuming. From previous studies, it has been shown that fatigue data from three or more stress ratios are required as training set to produce good fatigue life prediction results for the remaining stress ratios. Secondly, the NN capability for predicting fatigue lives for a wide range of different stress ratio values (generalization capability) is still often less satisfactory, even when more training sets have been utilized. In fact, the utilization of less training set is the most obvious advantage that NN can offer in the application of fatigue life prediction or could be a rational reason for one in using NN for assessing fatigue life.

No attempts have been made, so far, to utilize less training data set, yet at the same time yield reasonable fatigue life prediction results. More precisely, the utilization of fatigue data from only two stress ratios as training set and then using them to predict fatigue lives at several other stress ratios deserve attention.

The feasibility of this approach for different classes of polymeric-based composites and a wide range of stress ratios application is then assessed and discussed thoroughly.

1.4 Research Objectives

The primary objective of this research is to build an efficient MLP based NN model and use it to predict fatigue lives of polymeric-based composites under variable amplitude loading or different stress ratios condition, by utilizing fatigue data from only two stress

ratios-R as the training set. In addition, the study is to examine best training set of stress ratios giving better fatigue life prediction results with lower mean square error (MSE).

1.5 Scope of Study

In this study, the polymeric-based composites that investigated are E-glass/epoxy, E-glass/polyester and AS4/PEEK (polyether ether ketone). For several stress ratios-R, $R = 0.1, 0.5, -0.5, -1, -2$ and 10 for E-glass/epoxy, $R = 0.1, 0.5, 0.7, 0.8, 0.9, -0.5, -1, -2$ and 10 for E-glass/polyester, $R = 0.1, 0.2, -0.1, -0.3, -1$ and 10 for AS4/PEEK, the fatigue lives of the composites were assessed using Multi-layer Perceptron (MLP) based NN models, with the main structure of three layers consisting of input, hidden and output. The MLP architecture was chosen because it offered simple and efficient NN models. Moreover, from the above stress ratios, two stress ratios were selected and used as training sets. Therefore, the applicability of fatigue data with limited set of stress ratios consisting of only two stress ratios is being addressed in this study.

Besides their potential use in the engineering applications, the composite materials were selected in this study because the composites also represent different kinds of polymer-matrix, thermoset (for epoxy and polyester) and thermoplastic (for PEEK).

E-glass fabrics/epoxy and E-glass/polyester are typical materials used in wind turbine blade applications. Named as QQ1 and DD16, respectively, the materials represent the current and the earlier materials used in the applications. The QQ1 has higher fiber content than the DD16 and is more representative of the materials being used today. Moreover, the materials have been studied extensively in the past [10-12]. Meanwhile, AS-4/PEEK is commonly used for industrial and aerospace applications. Particularly for carbon fiber-reinforced PEEK composites, many fatigue experimentations have been conducted on with various laminate configurations [2, 13-18]. However, there is little exploration of NN used for predicting their fatigue lives. In relation with the increasing use of thermoplastic composites in polymer-based structural composites nowadays, the application of NN then should be also applied in predicting fatigue lives of these kinds of materials.

1.6   Benefits

The findings of the present study can result in economic saving in fatigue life assessment under variable amplitudes. Time and cost required for experimentation could be reduced significantly by the use of NN model which resulted in acceptable prediction results. Moreover, increasing confidence level for applying NN in predicting the composite fatigue life under real loading conditions in service, thus optimizing the use of composite materials in more hostile mechanical and thermal loading conditions.

1.7   Organization of Thesis

This thesis contains six chapters: *Introduction, Literature Review/Theoretical Background, Modeling using Neural Networks, Materials and Method, Results and Discussion* and *Conclusion*.

Chapter 1 presents the relevant research background and rational for the current study. Then, related problems in fatigue life assessment using NN are stated concisely in the problem statement section and so are the research objectives. Some key contributions from this study are also listed.

Chapter 2 provides thorough literature review and theoretical foundations for this study. It contains the recent works in the field application of NN for predicting fatigue life of composite as well as the discussion of composite and fatigue of composite materials, constant amplitude fatigue as well as constant life diagrams (CLD), which in particular gives an insight to the definition of a limited set of stress ratios.

Chapter 3 discusses the NN Architectures and Multi-layer Perceptron (MLP). The necessary explanation on issues pertinent to NN can be also found in this chapter. The derivation of back-propagation algorithm of the MLP and the pseudo-codes of Levenberg-Marquardt algorithm as the optimization method used in this study are presented as well.

Chapter 4 explains the details of the composites used (fibre material, matrix material and lay-up) and the fatigue test descriptions. In addition, the flowchart of NN modeling procedure is presented and the NN modeling related aspects are also described.

In Chapter 5, the results of fatigue life prediction for several stress ratios obtained using the proposed NN model are discussed and comparison to experimental data are made. The quality of the prediction results compared to the experimental data is measured using MSE. From the several stress ratios, the training set giving the smallest MSE is selected. Comparison with the corresponding MSE of the closely related previous works was also made. It is followed by sensitivity analysis that shows the applicable range of hidden node numbers for the current problem which is comparable to the ones from previous researchers. Important comments on the applicability of the NN modeling as well as a concise discussion on assessing the quality of NN prediction are also included.

Important conclusions from the NN modeling are finally drawn in Chapter 6. The necessary further research directions and recommendations are then highlighted.