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Machine learning based process monitoring and characterisation of automated composites

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ABSTRACT

There has been a huge uptake by industry groups to adapt automated fibre placement (AFP) based manufacturing due to it's high level of productivity, accuracy and reliability. The AFP technology merges through several manufacturing stages like cutting, curing and consolidation. The high level of productivity, accuracy and reliability in automated fibre placement (AFP) have opened new markets and applications for high value laminated composite structures.

However, from a system engineering perspective, manufacturing of composites using AFP is a complex, high-dimensional nonlinear multivariable process that involves large number of variables and parameters. The quality and integrity of the structure is critically dependent on the choice of these parameters, which are typically extracted by conducting several lab-based experiments with varied processing parameters. Appropriate selection of these parameters would provide optimal result.

Artificial neural network (ANN), a Machine Learning technique has been gaining popularity in various engineering applications including prediction, control, fault diagnosis etc. In this study, a multi-layer perceptron based ANN has been trained to accurately represent the complex relationship between various processing parameters in AFP that would give optimised outcome. The ANN model will subsequently be used to obtain the optimised parameters that can be integrated in AFP based manufacturing of laminated composite structures.

1. INTRODUCTION

With the increasing use of carbon/glass fibre-laminated composites for large components like wing skins, fuselages and fuel tanks in aircrafts and next generation of spacecrafts, digital manufacturing using robots is critical for mass production [1]. There has been a huge uptake by industry groups to adapt automated fibre placement (AFP) based manufacturing due to its high level of productivity, accuracy and reliability. The AFP technology merge through several manufacturing stages like cutting, curing and consolidation [2, 3]. Although the digital manufacturing using AFP has many advantages, the part quality is heavily dependent on the processing parameters [3-5].

Chen and Yousefpour [6] have highlighted the need to study the influence of process parameters on void content which have significant effect on microstructures and on the inherent properties of composite materials. Nixon-Pearson et al.[7], also have carried out a qualitative analysis on the void content after room temperature debulking and at elevated temperatures to investigate the feasibility of reducing hot debulk times. It has been shown that, the voids generally have low thickness with high in-plane dimensions. In the room temperature consolidation, the void content is at the highest level that decreases with increasing temperature under compaction by conditions consistent with hot debulking. Thus, having a good understanding of the process parameters and their influences make composite designers be able to improve their design quality to increase the buckling load, fundamental frequency [8] and reduce stress concentration effects [9], which leads to optimization of manufacturing process and structures [10].

However, AFP is a complex process in which the quality and integrity of the structure depend on proper selection of large number of variables that are extracted by conducting several coupon level experiments with varied processing parameters. Proper selection of these parameters, which would give desired optimal result, is a complex nonlinear optimization problem and has been a major research concern.

During the past few decades artificial neural network (ANN), a Machine Learning technique, has been gaining popularity for various engineering applications including prediction, control, fault diagnosis etc. The ANN is an efficient information processing paradigm inspired by the functioning of biological nervous systems, such as the brain. The key element of this paradigm is the novel structure of the information processing system, which is composed of a large number of highly interconnected processing elements (neurones) that has a natural propensity for storing experiential knowledge. These processing elements work in union to solve specific problems [11].

In this study, a multi-layer perceptron based artificial neural network (ANN) is trained to accurately represent the complex relationship between various processing parameters (thermal, mechanical and robot operation) in AFP to give optimised outcome. The ANN model will subsequently be used to obtain the best values of key parameters that will be integrated in AFP based composite manufacturing. This technique will be the first ever application of ANN towards the AFP process monitoring and parameter characterisation.

2. TECHNIQUES AND TEST METHODS

2.1 Operating Principle of Automated Fiber Placement Machine

Automated Fiber/Tape placement is one of the advanced manufacturing methods for making large composite components. In this method, several manufacturing stages are incorporated in the placement head, as shown in Figure 1. The machine includes compaction roller, heating system and a robotic arm, which is computer controlled [12-14]. In this process, an incoming tape is bonded to the previously laid and consolidated ply under pressure and temperature, provided through the compaction roller and heat source respectively. In this study, a hot gas troch (HGT) based heat source was utilized that delivers high temperature (up to 950 ºC) nitrogen through a nozzle around the tape to initiate the polymerisation. A number of parameters influence the quality of laminate manufacturing using the AFP machine. These parameters include, but not limited to, curing/melting temperature, consolidation force, feed rate, heat flow rate, ply orientation and lay-up speed.

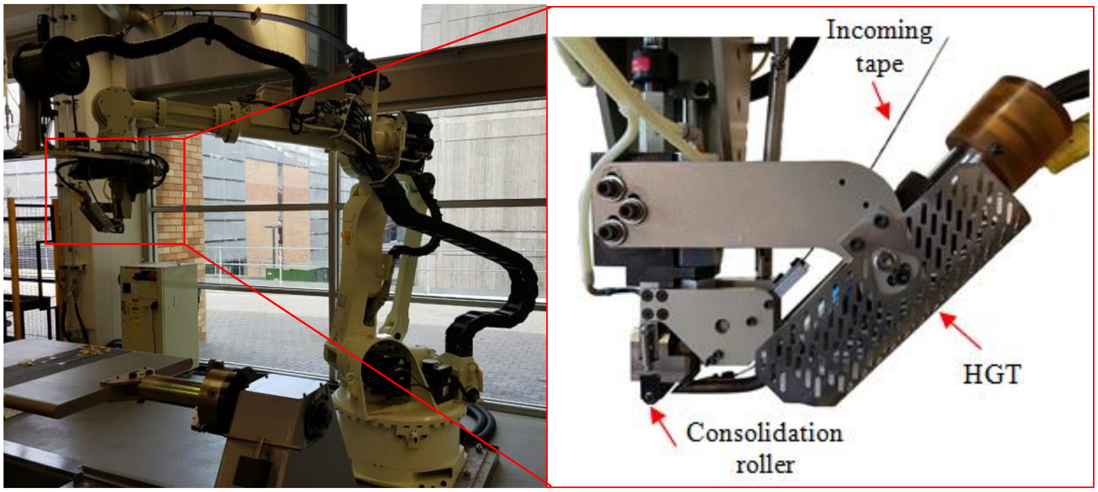

Figure 1. Automated fibre placement (AFP) machine with the thermoplastic (TP) head; (Photo courtesy: UNSW Sydney).

2.2 Machine learning based training towards automated manufacturing

Artificial neural network is an effective machine-learning tool that can be used to mimic the complex relationships of a manufacturing process. A neural network is an assembly of a large number of highly interconnected simple processing units called neurons. The connections between the neurons have numerical values, which represent the strength of these connections known as weights. The knowledge about the intricate relationships between a number of variables/parameters of a manufacturing process are encoded in these weights. These neural networks are capable of self-organisation and knowledge acquisition. These capabilities of the neural network are exploited for AFP based manufacturing of laminated composites in this study. The basic principle of the proposed method will be discussed in the following sections which are being used to update the weights. The training mechanisms of ANNs are available in various open resources [11, 15, 16].

3. EXPERIMENTAL PROGRAM

The influence of processing parameters on the mechanical characteristics of AFP fabricated laminated composites is investigated first to establish the experimental demonstration. In the preceding section we highlighted about the quality and integrity of fabricated laminates that are critically dependent on the appropriate selection of three key processing parameters such as HGT temperature, consolidation force and lay-up speed.

3.1 Material

The unidirectional (UD) thermoplastic prepreg used in this experiment was carbon fibre reinforced polymer, CF/PEEK (AS4/APC2) supplied by Cytec. The prepreg has fibre volume fraction of 0.6 with 6.35 mm width and thickness of 0.15 mm. The other material properties including density, module of elasticity, shear modulus and Poisson's ratio are 1570 kg/m^3, 138 GPa, 5 GPa and 0.28 respectively.

3.2 Sample preparation

For this experimental program, eight samples were manufactured using the Automated Dynamics built AFP machine, shown in Figure 1. The lay-up procedure using thermoplastic head and the manufactured laminates are shown in Figure 2(a) and 2(b). Each sample consists of twenty-one plies of unidirectional prepreg tapes. All the tapes were laid unidirectional (0/0) to each other. The prepreg plies are processed simply by heating and cooling cycle. To study the relationship between the process parameters and the mechanical properties, eight different consolidation conditions were used which is shown in Table 1. In all of these conditions, the material (tape) deposition rate was kept constant at 76 mm/s while the temperature and consolidation force were varied. The actual temperatures corresponding to each of the adjusted HGT temperature also are shown in the Table 1. The overall dimension of each sample was 200 (Length) x 6.35 (Width) x 3.15 (depth) millimeters. The samples were then cut to ten coupons (19 mm x 6.35 mm x 3.15 mm) using a diamond saw.

Table 1. The processing conditions for manufacturing the thermoplastic laminates.

Lay-up process conditions

Processing Condition No.	Deposition Rate (mm/s)	HGT Temperature (ºC)	Actual Temperature (ºC)	Consolidation Force (N)	Number of UD prepregs
C1	76	950	~515	180	21
C2	76			250	21
C3	76			350	21
C4	76			450	21
C5	76	850	~415	180	21
C6	76			250	21
C7	76			350	21
C8	76			450	21

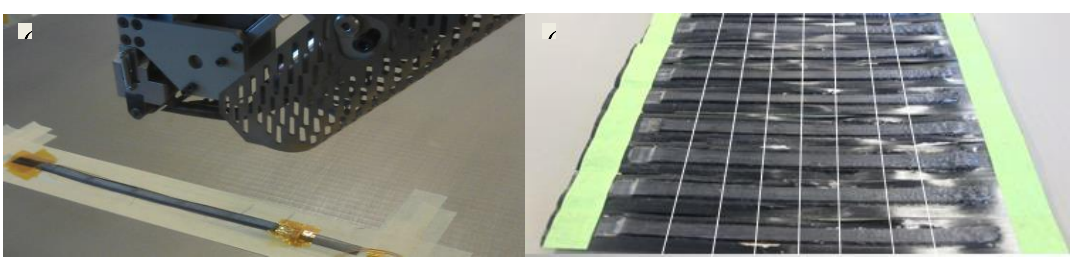

Figure 2. (a) AFP Lay-up process; (b) AFP manufactured laminates before cutting.

3.3 Experimental set-up

The laminated composite test coupon samples were loaded into a test fixture which is specially designed to perform the Short Beam Strength (SBS)/Interlaminar Laminar Shear Strength (ILSS) test using Instron 50KN test machine. The experimental setup for analysing the mechanical characteristics of AFP manufactured laminates is shown in Figure 3. All specimens were tested at constant loading rate of 1 mm/min in displacement control mode. Through the experiment, the elastic modulus of five coupons from each sample were determined in accordance to ASTM-D2344. The short beam strength /interlaminar shear strength (ILSS) of each coupon was calculated using equation (1) [17]:

$$F^{sbs} = 0.75 \times \frac{P_m}{b \times h} \qquad [1]$$

where F^{sbs} is the short beam strength/interlaminar shear strength; P_m is maximum flexure load; b is the specimen width and h is the specimen thickness. Additionally, the maximum flexural stress and strain were calculated based on ASTM-D7264 using equations (2) and (3) respectively [18]:

$$\sigma = \frac{3PL}{2bh^2} \qquad [2]$$

where σ is the stress at the outer surface in the mid-span; P is the applied force; L is the support span; b is the width of beam and h is thickness of the beam.

$$\varepsilon = \frac{6\delta \mathrm{h}}{L^2} \qquad [3]$$

where ε is maximum strain at the outer surface; δ mid-span deflection; L is the support span and h is the thickness of beam. The input and output data from this experimental program is utilised for the ANN system training whose behaviour including inputs & outputs evolved over a period. Then, for a set of new inputs to the ANN, the model/system identification tries to find the optimal outputs. It is also capable of approximating any complex nonlinear process or system.

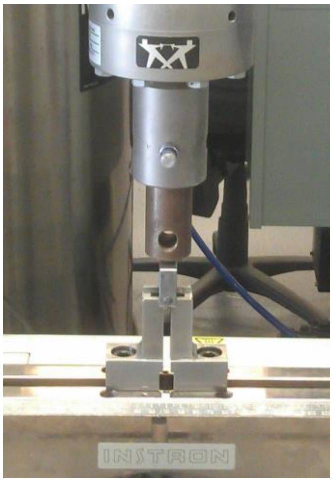

Figure 3. Experimental set-up for the SBS/ILSS test using Instron 50KN.

3.4 ANN Problem formulation

In the present study, the problem of automated manufacturing is projected as a system identification problem as shown in Figure 4.

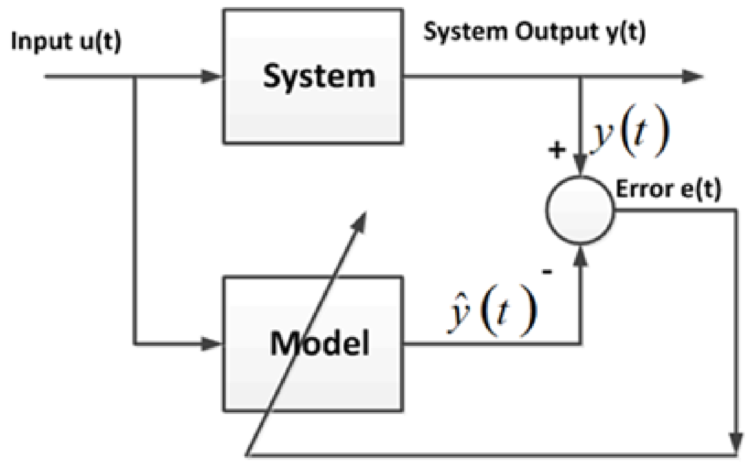

Figure 4. Philosophy of System Identification.

The block '**system'** in Figure 4 represents the manufacturing process or the sample. The input/inputs to this are various processing conditions such as lay up speed, curing temperature, consolidation force etc. The outputs of the system are ILSS, elastic modulus, maximum flexural stress and strain. The basic philosophy of this approach is to apply a set of input/inputs both to the system/process/sample as well as to the model and compare the outputs of the model with those obtained experimentally from the system/sample. The parameters of the model are updated using the error until it becomes zero (ideally). To further clarify the proposed approach, consider the schematic shown in Figure 5 where the model, which is used to mimic the manufacturing mechanism, is a 4-input-2-output neural network. For a given set of inputs i.e. manufacturing conditions, the outputs of the neural network are compared with those obtained from the experiment and the weights/parameters of the neural network are updated until the error becomes ideally zero [15] .

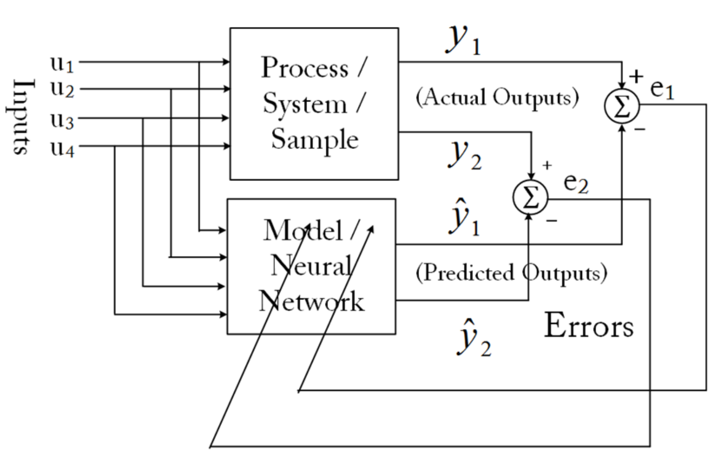

Figure 5. Neural Network Based System Identification / Automated Manufacturing.

4. RESULTS AND DISCUSSION

4.1 Static characterization of laminated composites

The experiments were conducted on the coupons (CF/PEEK), made under eight different processing conditions (Table 1). Three point bend tests were carried out using Instron 3369-50KN uniaxial machine at 1 mm/min rate of loading. The summary of the results for mechanical characterisation, that are obtained through the experiments, is illustrated in Figure 6. The mechanical charactrisations include the following mechanical properties; (a) elastic modulus; (b) interlaminar shear strength; (c) maximum flexural stress; (d) maximum flexural strain.

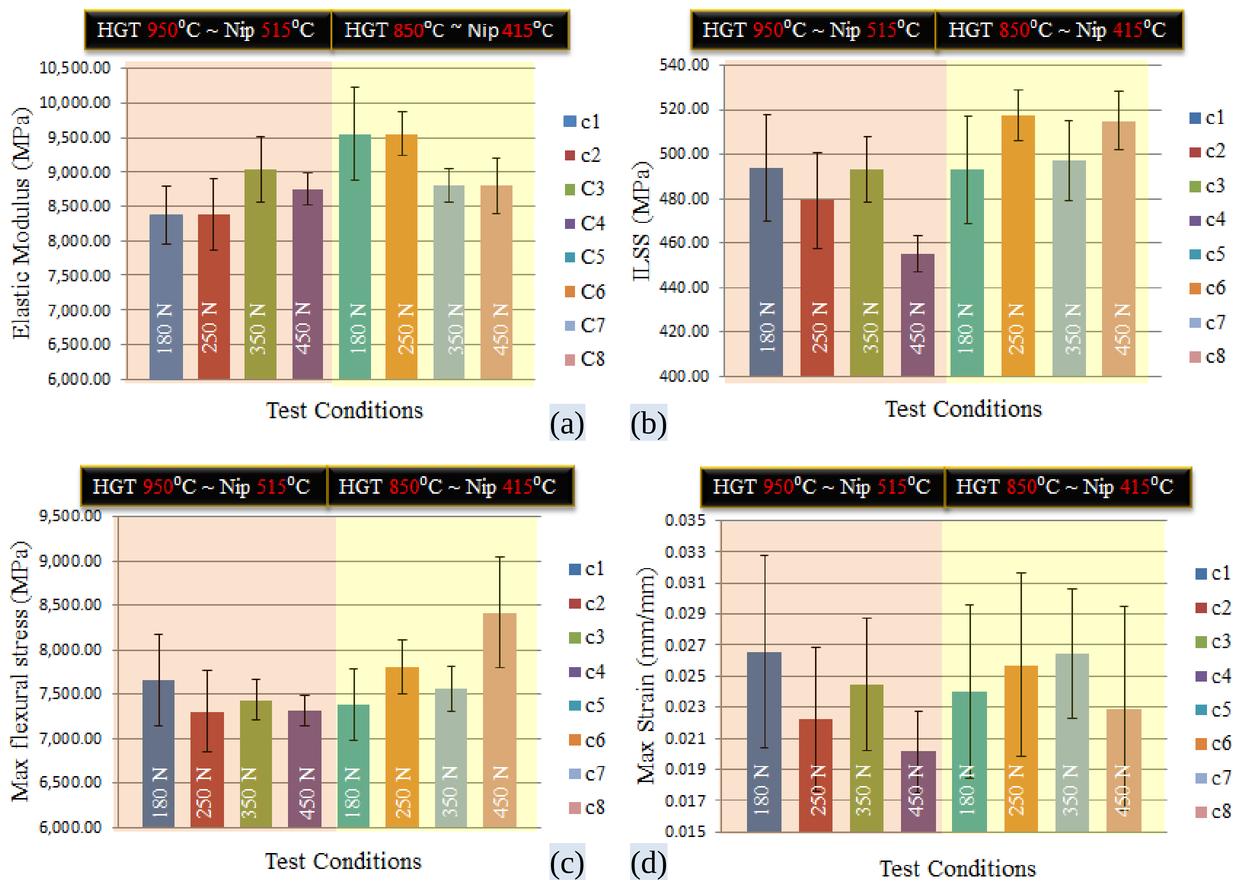

Figure 6. The summary of mechanical test results: (a) Elastic Modulus; (b) Interlaminar shear strength (ILSS); (c) Maximum flexural stress; (d) Maximum flexural strain.

Since the deposition rate of composite material using AFP was kept constant, there are only two competing factors which will have non-linear effects on the overall mechanical properties. It is observed that for all test conditions, 850 ºC HGT processing yield superior elastic modulus, ILSS, flexural stress and maximum strain. This observation is consistent with the fact that the actual temperature in this condition is much closer to the process temperature of tape material (382 ºC - 400 ºC). Consequently, better consolidation takes place under these loading conditions. At higher temperatures i.e. more than the processing temperatures, result in thermal degradation of the polymer (at least above a certain point) which will consequently decrease the ILSS. Of all the conditions investigated in this experimental program, it was found that conditions C6 and C8 (ref Table 1) can provide higher ILSS compared to others (Figure 6-b). It is evident that with the lower HGT, the consolidation force may need to be increased to achieve same level of ILSS. Another possible alternative to increase ILSS at lower temperatures could be achieved by decreasing the deposition rate of material which can provide longer time for the resin to flow and interact with the fibres across the interface.

4.2 Artificial neural network approach

The effectiveness of the proposed neural network/machine learning based process monitoring and characterisation of automated composites is demonstrated based on the experimental results for eight different processing conditions (C1-C8). The processing conditions such as lay up speed, HGT and consolidation force are called as inputs and the parameters like interlaminar shear strength (ILSS), elastic modulus, maximum flexural stress and strain are called as outputs. Since the available experimental data were limited, they were repeated five times to get 192 pairs of input-output data. In this study, the performance of different type of ANN such as feed forward neural network, NAR and NARX ANN with varying number of hidden layers and neurons have been investigated to train the mechanical performance of the composite laminates. It was found that amongst all these NNs, NARX ANN gave the best results as have been presented in the Figure 7-9. The complex relationships of various processing parameters are established for the first time, following the system identification and machine learning approach. There appears to be no base case where the performance of the proposed approach can be compared. However, since model validation is an important stage of system identification, in this study we have used cross validation [19] technique to validate the model. In this technique, the available data set is divided into two sets, the estimation and the test (validation) set. The estimation set has been used for fitting the ANN and the test set is being used to validate the model.

These input-output data which was produced experimentally were used to train a NARX artificial neural work (ANN) [20] with 10 hidden neurons and one hidden layer with 3 numbers of output delays and zero input delays. The number of input neurons is equal to the number of inputs and number of output neurons is equal to the number of outputs. For a single category of output (Ex: elastic modulus) samples C1- C5 were treated as different outputs and average was also considered as an output due to lack of training data (total of 240 pairs of input-output data). It may be noted that the inputs are the same but the outputs are different for each sample under each test condition.

The data set was divided into two sets; estimation and test (validation) sets. Initially, a multiple input single output NARX ANN was trained using Levenberg-Marquardt training algorithm considering the elastic modulus as the output using the estimation data set. The mean squared error in the output was computed by comparing the expected sample output for a particular test condition with NN output, using Neural Network toolbox in MATLAB. The model was validated using the test (validation) data set and the results are shown in Figure 7. From the results, it is obvious that NN can be used to determine the optimal parameters for manufacturing automated composites. NN is over-fitting after some epochs since the same data was repeated. With sufficient number of training data NN approach can be used effectively to determine the optimal parameters for manufacturing automated composites.

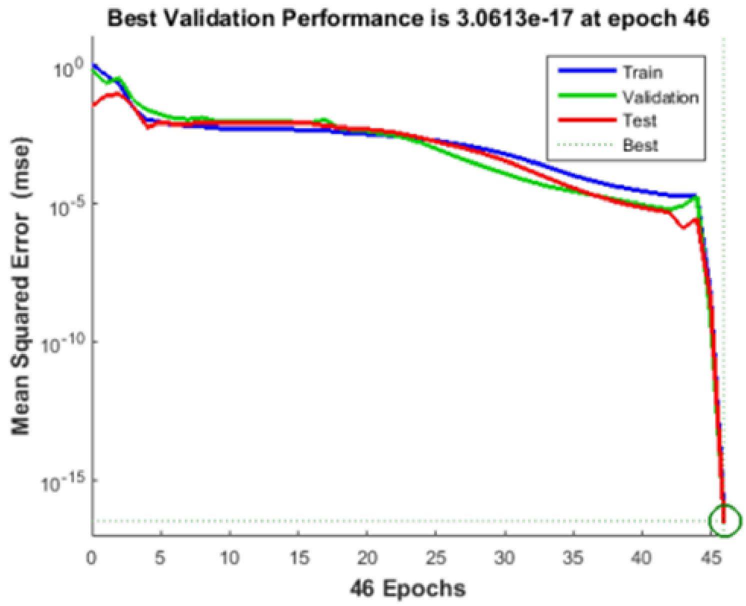

Figure 7. Mean Square Error of fitting a 4-Input Single Output (Elastic Modulus) NARX ANN.

Next, a multiple input two output NARX ANN was trained considering ILSS and elastic modulus as outputs using Bayesian regularization training algorithm. The mean squared error in the outputs were computed by comparing the expected sample outputs for a particular test condition with NN outputs, using Neural Network toolbox in MATLAB and the results are shown in Figure 8. NN is over-fitting after some epochs since same data was repeated. From the result it is evident that NN network can be used effectively for a two outputs case with sufficient number of training data.

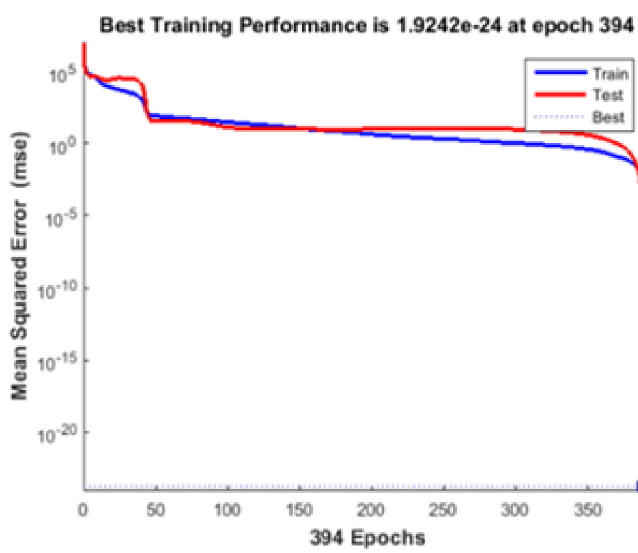

Figure 8. Mean Square Error of fitting a 4-Input 2-Output (ILSS, Elastic modulus) NARX ANN.

At the final stage, a multiple input 3-output NARX ANN was trained considering ILSS, elastic modulus, maximum strain as outputs using Bayesian regularization training algorithm. The mean squared error in the outputs were computed by comparing the expected sample outputs for a particular test condition with NN outputs, using Neural Network toolbox in MATLAB and the results are shown in Figure 9. From the result it can be seen that with higher number of outputs it is getting harder to train the NN thus over-fitting cannot be seen. But, with sufficient number of training data the results from a NN with higher number of hidden neurons may be more convincing.

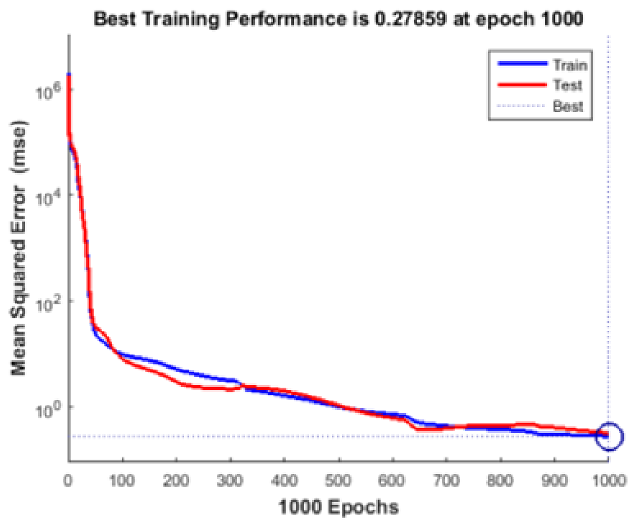

Figure 9. Mean Square Error of fitting a 4-Input 3-Output (ILSS, Elastic modulus, Max Strain) NARX ANN.

5. CONCLUSIONS

In this experimental study, artificial neural network (ANN), as an effective machine learning tool, was implemented to mimic the complex relationships of manufacturing process parameters in AFP. For this purpose, carbon-fiber composite laminates were fabricated using different processing conditions. The mechanical characterization of AFP fabricated samples are investigated through the laboratory based mechanical tests. In the ANN system, the processing conditions (lay up speed, HGT temperature, consolidation force) are called as inputs whereas the obtained results from the mechanical tests (ILSS, elastic modulus, etc.) are defined as outputs. With the limited amount of available experimental data, it can be seen that artificial neural network could effectively capture the underlying relations between various variables. However, it was observed that as the number of outputs increase, the number of epochs eventually increases. The Levenberg-Marquardt training algorithm which was used for single output case could not effectively train the network with more number of outputs. Therefore, Bayesian regularization training algorithm was used while considering multiple outputs. The sudden dip in the first two cases is probably due to the over-training. With a sufficient number of training data points, the proposed neural network approach can be used to determine the optimal parameters for automated composites.

6. ACKNOWLEDGMENT

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