

Using Neural Networks to Examine the Sensitivity of Composite Material Mechanical Properties to Processing Parameters

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ABSTRACT

Successful manufacture of Carbon Fibre Reinforced Polymers (CFRP) by Long-Fibre Reinforced Thermoplastic (LFT) processes requires knowledge of the effect of numerous processing parameters such as temperature set-points, rotational machinery speeds, and matrix melt flow rates on the resulting material properties after the final compression moulding of the charge is complete. The degree to which the mechanical properties of the resulting material depend on these processing parameters is integral to the design of materials by any process, but the case study presented here highlights the manufacture of CFRP by LFT as a specific example. The material processing trials are part of the research performed by the International Composites Research Centre (ICRC) at the Fraunhofer Project Centre (FPC) located at the University of Western Ontario in London, Ontario, Canada. The experimental processing system is instrumented to record data in three zones of the machine, including temperatures, torques, speeds, forces, and pressures. Material processing trials for six different fibre volume weights were conducted and the mechanical properties of the material were measured in both the zero and ninety degree fibre directions. A neural network model relating the processing parameters (as model inputs) to the mechanical properties of the material (as model outputs) was developed. As a result, the sensitivity of the material's mechanical properties to the processing parameters could be examined as part of the model optimization process. The results of the sensitivity study are presented here along with a discussion of the further reaching implications on design tool development for composite materials.

CITATION: Zhang, X. and Johrendt, J., "Using Neural Networks to Examine the Sensitivity of Composite Material Mechanical Properties to Processing Parameters," *SAE Int. J. Mater. Manf.* 9(3):2016, doi:10.4271/2016-01-0499.

INTRODUCTION

Composite materials are widely used in mechanical engineering to satisfy specific design requirements. Composites are a combination of two or more materials with different properties, whose combination produces a new material with beneficial properties for specific applications. In the automotive and aviation fields, lighter, stronger and lower cost materials are always required, making composites an obvious choice. Fiber-reinforced polymer (FRP) material can be used in the manufacture of chassis, body, and engine components. For chassis components, many researchers have used FRP composites in the manufacture of leaf springs and drive shafts. The high temperature requirement of the matrix (i.e. resin) component is a challenge for composite engine components. Due to the complex structure and complicated manufacturing process of FRP materials, material analysis cannot be accomplished with the same methods as metallic materials, for example. Therefore, there is a need for a simplified model that can accurately relate manufacturing process parameters to the FRP material performance.

Artificial Neural Networks (ANNs) are such a tool that can be used to predict mechanical properties of composite materials in this way [1,2]. This black-box model has many advantages like global optimal searching and quick convergence speed [1-3]. Additionally, ANNs can be applied not only in the study of mechanical properties but

wherever the complexity of a problem is overwhelming from a fundamental perspective and where over-simplification is unacceptable in the face of reduced accuracy [4-7].

One goal of the current research is to use ANNs to determine the relationship between FRP performance and the manufacturing process parameters by using the sensitivity analysis calculated from ANN results. By using ANNs, the sensitivity of CFRP mechanical properties to LFT-D (Direct Long Thermoplastic Molding) processing parameters can be calculated in order to further analyze the relationship between the properties and the processing parameters. As such, ANNs were developed relating the LFT-D processing parameters (as model inputs) to mechanical properties of the material (the model outputs). The sensitivity was calculated from the results of the trained ANN.

LFT-D PROCESSING OF CFRP

The LFT-D line produces charges that are compression molded. These charges consist of mixed melted polymer and preheated continuous carbon fibers. The hydraulic press is a high-speed compression mold in which the charge is placed. In practice, the hydraulic press can fabricate a carbon-fiber composite panel in as little as 30 seconds.

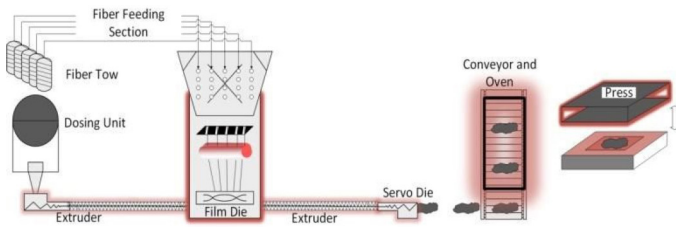


Figure 1. Process scheme of LFT-D line.

As Figure 1 shows, throughout the fiber feeding section, the continuous fiber is fed into the extruder from the fiber tow, where it is mixed with the polyamide. The polyamide, coming from the dosing unit, is melted as it passes through the heated extruder. At the second extruder, the fiber is mixed in a set direction with the melted polyamide and the charge is produced for the press. The charge goes in the oven on a conveyor, and then charge put into the press machine where the panel is produced.

The LFT-D process, as mentioned, is a highly automated process for thermoplastic-matrix composite material production. The LFT-D line at FPC is instrumented so that processing parameters can be measured throughout the process. There are three distinct sections (ZSG, ZSE, and PAZ) that make up the LFT-D line. The processing parameters are set before each run.

Fifty-two LFT-D processing parameters were used in the current research, including temperatures, speeds, torques, and flow rates. These 52 parameters can be divided into three categories according to their location in the system: ZSE (the polymer feeding zone), ZSG (the fiber feeding and material mixing zone), and PAZ (the mixed material separation and delivery zone).

Additionally, the 52 input parameters are set for six different trials classified by the fiber volume weight for each trial. Thus, the data is organized as shown in [Appendix A1](#). Data was normalized before network training and simulation.



Figure 2. Carbon fiber in rovings prepared for LFT-D feeding.

Figure 2 shows fiber tow on centre pull spools as it is fed into the LFT-D line. Generally, continuous long fiber (fiber tow) is more easily fed. Unless the fiber is fed smoothly into the machine, the mechanical properties cannot be guaranteed. Figure 3 shows the press charge produced by the LFT-D line. The weight and the fiber volume of the charge can be set. Commonly, using an oven to maintain the temperature of the charge ensures the quality when entering the press. In Figure 4, the black panel is the material produced by the LFT-D trial. These panels are also the test panels from which samples were cut and data measured for the current research.



Figure 3. Charge produced by LFT-D prepared for the press.

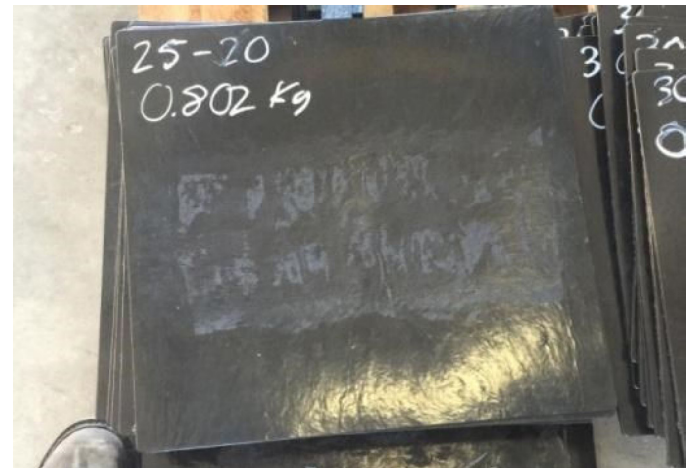


Figure 4. Test panels produced by the LFT-D process.

NEURAL NETWORKS

After exploring ANN structures, the architecture of the ANN was designed to include the logsig transfer function in the hidden layer of 105 neurons, the feed-forward backpropagation (FFB) network structure and four output parameters, Young's modulus and tensile strength of the material in the 0° and 90° directions (i.e. a 52-105-4 configuration). [7-10] Table 1 lists the training parameters used during neural network development.

Table 1. Network training parameters.

Target Data	Young's modulus & tensile strength at 0° and 90° fiber orientation
Input Data	LFT-D process parameters for fiber volume weights 25% 30% 35% 40% 45% 50%
Network Type	Feed-forward backpropagation (FFB)
MATLAB Training Function	Trainlm (Levenberg-Marquardt)
Performance Function	Mean Square Error (MSE)
Number of Hidden Layers	1
Number of Input Neurons	52
Number of Hidden Neurons	105
Number of Output Neurons	4

The 52 normalized inputs (processing parameters) were based on mean values. The network outputs were derived from raw test data. The network structure is shown in Figure 5.

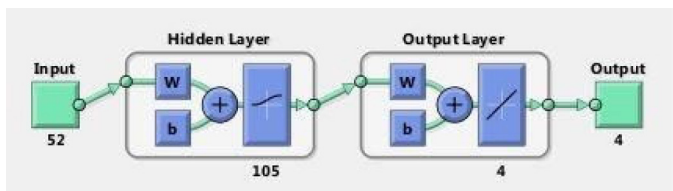


Figure 5. Neural network structure for training.

The training results are listed in Table 2. The best performance is the MSE calculated at the epoch when the validation check stops the iterative training process. The performance is the final MSE calculated after the network training is complete. If the performance curve after best performance of the validation check still decreases sharply, it may mean that the network is over-fitting the target data and further investigation would be required.

Table 2. Performance of the mean value data trained result

Training Function	LM
Best Performance (MSE)	0.18559
Epoch at Best Performance	1
Performance (MSE)	0.0478

NEURAL NETWORK TRAINING FOR SENSITIVITY ANALYSIS

To examine the sensitivities of the network outputs relative to the inputs for the selected network structure, a randomly generated input is added to the input data. In this way, the relevance of each input parameter relative to a random value can be evaluated.

The FFB network is one of the simplest structures but is very effective when compared with other, more complex, types of networks. Training time and performance associated with the

Levenberg-Marquardt training function make it a popular choice of researchers. The use of mean value for both the input and the output datasets gives a better and more generalized performance results than individual values.

With the additional randomly generated input, the network training used a 53-107-4 logsig configuration with the LM training method as described in the previous section. Once again, the inputs included the mean values of the processing parameters with the addition of a randomly generated input. The process was 16 seconds until the gradient achieve the default setting value. At this time there were two validations. The final performance was 0.0617 at the last epoch. The best validation performance of this training was 0.1036 at epoch 1. There were three epochs during training. Due to reaching the minimum gradient of the MSE, the network training stopped with results in an acceptable range.

Figure 6 gives the results of the network training, with the regression between the target and network output illustrating how well the network trained.

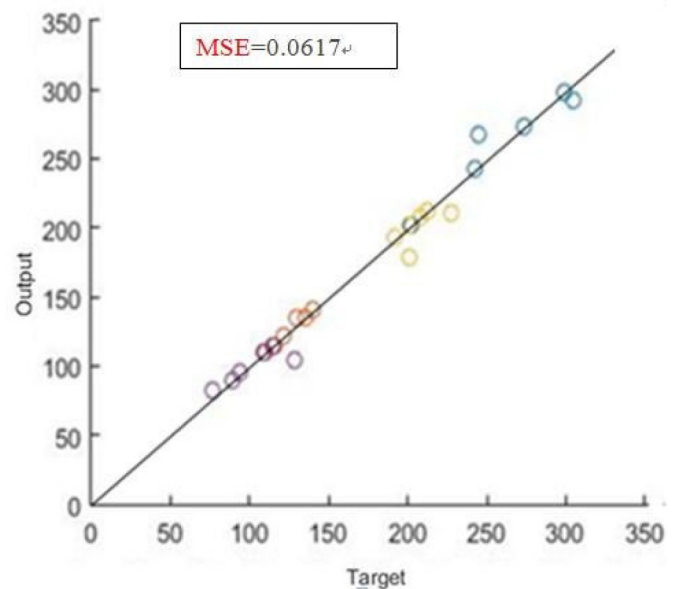


Figure 6. Regression of network training results (un-normalized original data)

Sensitivity Analysis

The neural network is now used to find the relationship between the LFT-D processing parameters and the CFRP properties. When developing the neural network, all inputs are used to predict the outputs. To simplify the network, the sensitivity of each output to each input can be calculated to determine if any of the inputs can be eliminated from the model due to a lack of influence on any of the output variables. The sensitivity is expressed as the partial derivative of each network output with respect to each of the inputs [11,12].

The sensitivity can provide information as to the relative influence of each network input on each network output. The greater the sensitivity is, the greater the connection between each pair of input-output parameters.