ULTRASONIC WELDING OF CF/PEKK TO CF/EPOXY THROUGH OPTIMISATION USING MACHINE LEARNING

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ABSTRACT

The application of fibre-reinforced thermoset material systems has been established in the aerospace industry, e.g. primary structure on commercial aircrafts. However, there is an increasing interest in thermoplastic-based material systems due to their potential for fast forming, weldability, their inherently superior fatigue performance, and excellent fire/smoke/toxicity (FST) properties. Current repair techniques for thermoset panels are adhesive bonding and mechanical fastening. However, these techniques are limited when applied to thermoplastic composites as mechanical fastening leads to stress concentrations and localized delamination which is worse for thermoplastic composites. In this paper, the optimisation of dissimilar material was carried out using a hybrid genetic algorithm – artificial neural network (GA-ANN) model. Due to the complexity of the ultrasonic welding (USW) process, Bayesian optimisation is adapted to determine the most suitable ANN architecture to develop a robust model. The predictive model is developed to map the relationship between welding energy, vibration amplitude, and welding force to the corresponding Lap Shear Strength (LSS). The model was trained on 27 experiments using the leave-one-out cross-validation method to measure the model's ability to generalise. To evaluate the optimised joint performance, The bonded joints were tested to determine the tensile load carrying capability, and their failure modes were analyzed with the primary aim to develop an efficient repair joining methodology.

1 INTRODUCTION

The use of composite materials is increasing at an unprecedented rate in aerospace, automotive, and many other commercial industries. The interest in using thermoplastic composites in primary aircraft structures is also increasing, due to their cost-effectiveness in manufacturing. Currently, most primary aerostructures are manufactured from thermoset composites and they cannot be joined to thermoplastic composites. The current joining methods used are mechanical fastening and adhesive bonding, however these current joining techniques employed for composite materials are also labor intensive and dependent on operator skill [1], [2]. A more efficient approach to join composites must be developed to improve manufacturing efficiency and the structure's overall performance.

Ultrasonic welding (USW) is a solid-state joining technique that uses high frequency (10-70 kHz), small amplitude vibrations (10-250 μm) which is dissipated as heat at the interface of the specimens being joined [3]. USW is an efficient joining process as it does not require any surface preparation or add additional mass to the structure. The process can be automated, resulting in faster production times and lower labor costs [4]. USW is a technique that can potentially offer an economical and effective thermoplastic composites repair process, due to its short welding time, ease of automation, and excellent bond quality.

One advantage of using automated techniques for joining is that predictive modelling through ANN can be used to predict and optimize the process. USW is a convoluted process that is difficult to optimize, therefore, requires extensive data analysis to understand the underlying bonding mechanisms. Joining dissimilar materials exhibits additional challenges as the underlying bonding mechanisms are complex leading to intricate relationships between process input parameters and process performance. Various researchers have employed ANN architectures to model complex manufacturing processes. Mongan et al., developed an ANN model to predict the performance of USW aluminum joints [5]. The study demonstrated a high level of accuracy with a correlation coefficient of 0.9827 between the predicted and actual values of lap shear strength (LSS). Zhao et al., developed an ANN to predict the performance of USW dissimilar materials (aluminum 6061 to A36 steel) [6]. The study also demonstrated a high level of accuracy in its predictions with a correlation coefficient of 0.99842. However, the above studies did not employ the model to optimize the process, the models were used to predict random parameter groups.

The experimental study presented in this paper is aimed at investigating ultrasonic welding of dissimilar CF/PEKK to co-cured CF/Epoxy. The optimization of dissimilar material was carried out using a hybrid genetic algorithm – artificial neural network (GA-ANN) model. Due to the complexity of the welding process, Bayesian optimization is adapted to determine the most suitable ANN architecture to develop a robust model. The predictive model is developed to map the relationship between welding energy, vibration amplitude, and welding force to the corresponding LSS. The model was trained on 27 experiments using the leave-one-out cross-validation method to measure the model's ability to generalize. To evaluate the optimized joint performance, fracture surface analysis and microscopy were performed at the joint interface.

2 MATERIALS AND METHODS

2.1 Materials and manufacturing

The materials used in this study are Tenax®-E HTS45 carbon fibre reinforced polyetherketoneketone (CF/PEKK) and Hexcel IM7 carbon fibre reinforced HexPly® 8552 epoxy (CF/Epoxy). Table 1 summarises the different attributes of CF/PEKK and CF/PEKK prepregs from the supplier's technical data sheet. Additionally, a 125 µm thick Sabic Ultem 1000 polyethermide film (PEI) was used as a part of this study.

Table 1: Specifications of material used

Prepreg	Matrix content	Fibre volume fraction	Consolidated ply thickness	Glass transition temperature
CF/PEKK	34 wt%	60%	0.184 mm	162°C
CF/Epoxy	34 wt%	60%	0.120 mm	154°C

Flat panels were manufactured using a standard autoclave consolidation process with a stacking sequence of $[0]_{12}$ and $[-45/0/+45/90]_{4S}$ for the CF/PEKK and CF/Epoxy, respectively. The panels were vacuum-bagged using high-temperature polyimide bagging material and sealant tape. The consolidation temperatures used for PEKK and Epoxy prepregs were respectively 365 °C and 180 °C, while the consolidation pressure and dwell duration were 600 kPa and 60 min, respectively. The temperature and pressure ramp-up and ramp-down rates were 3 °C/min and 50 kPa/min, respectively. For the CF/Epoxy laminates, the PEI film was co-cured as they were compatible with both PEI and PEKK and promotes the formation of stronger joints [7]. The consolidation pressure and temperature were monitored throughout the processing cycle. The specimens were extracted from the composite panels using an abrasive waterjet cutting process.

2.2 Ultrasonic welding

A 2000 xdt Branson Ultrasonic welder at the University of Limerick was employed for the joining of the CF/PEKK to CF/Epoxy. The output frequency of the machine was 20 kHz and maximum power of 4000 W. The diameter of the sonotrode was 40 mm. The ratio of the gain for the booster and the horn were 1:2 and 1:3, respectively. Figure 1 shows the schematics of the ultrasonic welder and the weld specimen geometry.

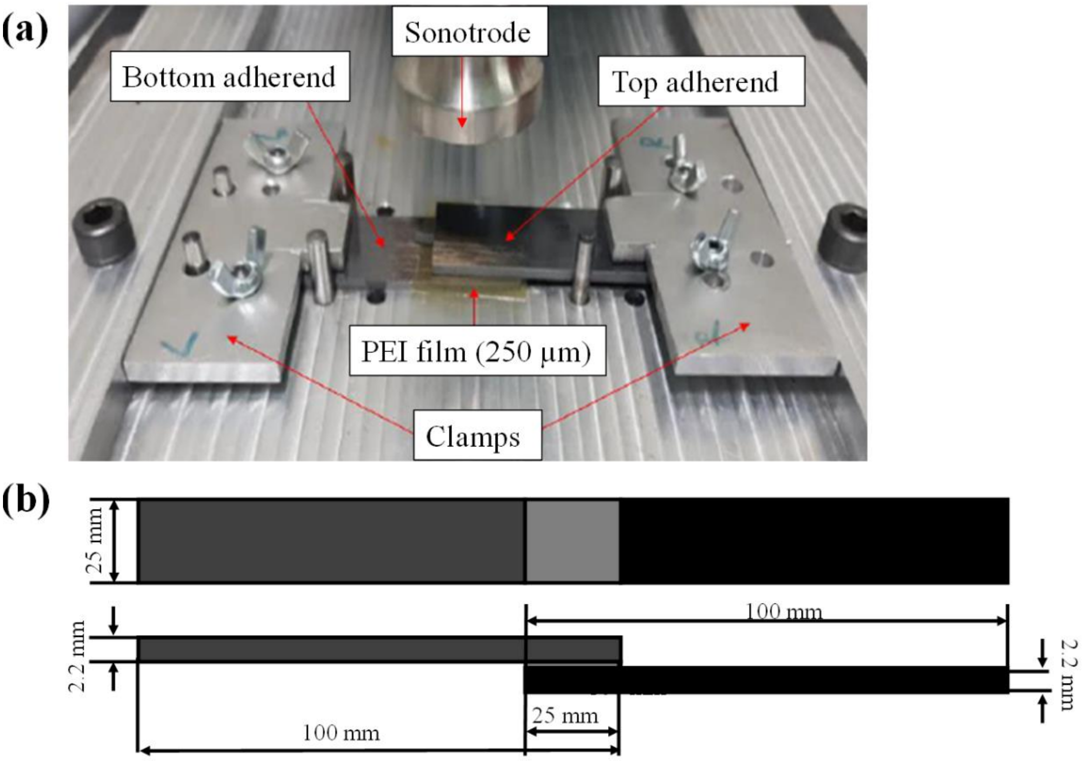


Figure 1: Schematics of (a) ultrasonic welder (b) joint configuration

For joining of the dissimilar materials, welding optimisation was performed using the energy mode. A preselected energy was chosen and input in the machine, when the specimen absorbed the energy, the ultrasonics stopped and consolidated for 3 s at a similar force to that of the welding force. A Design of Experiment (DOE) was carried out by varying three input parameters: energy, amplitude, and welding force. Optimisation studies for ultrasonic welding [8]–[10] have shown these input parameters being a critical in affecting the weld strength of the joint. Preliminary tests were performed to determine the minimum and maximum values for the three inputs shown in Table 2. The adherends below the minimum and maximum values showed no consolidation or degradation of the material respectively. A median level was selected that was between the minimum and maximum level. To derive a relationship between the three input parameters, a series of experiments with an array of 3^3 were performed with 3 repeats at each parameter and tested for their strength. Table 3 shows the different weld input parameters. The lap shear strength (LSS) of the joints were determined using a Zwick 100 kN tensile tester with a crosshead speed of 13 mm/min in accordance with ASTM D 5868.

Table 2: Minimum and maximum values for DoE

Input parameters	Minimum	Median	Maximum
Welding energy (kJ)	1	1.75	2.5
Welding force (N)	400	800	1200
Vibration amplitude (µm)	85	100	115

Table 3: DoE input parameters

Run Order	Energy (J)	Force (N)	Amplitude (µm)
1	2500	800	85
2	1750	800	85
3	1750	1200	115
4	1750	800	100
5	2500	800	115
6	1000	800	115
7	2500	800	100
8	1000	800	100
9	1000	800	85
10	2500	400	85
11	1750	400	100
12	2500	400	115
13	1000	400	85
14	1000	400	100
15	1750	400	115
16	2500	400	100
17	1000	400	115
18	1750	400	85
19	1750	1200	115
20	1750	1200	85
21	2500	1200	115
22	2500	1200	100
23	2500	1200	85
24	1000	1200	85
25	1000	1200	100
26	1000	1200	115
27	1750	1200	100

2.3 Machine learning

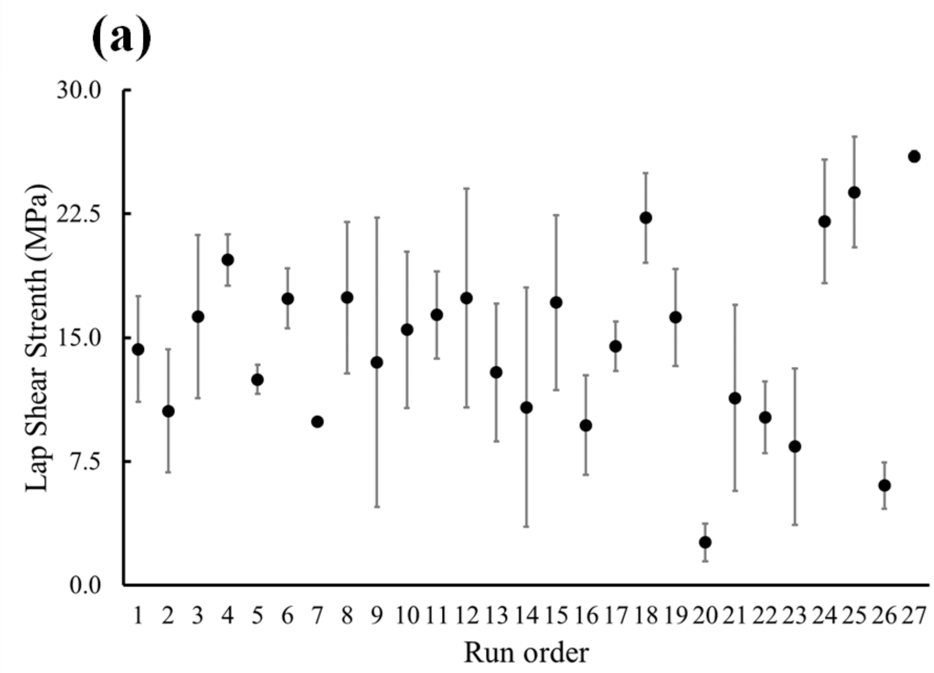
A GA-ANN model was developed to map the convoluted relationship between the input parameters and joint performance. The following provides a brief overview of the methods used to develop the GA-ANN model and is based on [11] where a detailed description of the predictive modelling aspect of this study can be found. The hyperparameters of the ANN are key elements affecting the model's prediction performance. Manufacturing processes with complex relationships between input parameters and process performance indices require extensive analysis to accurately identify suitable hyperparameters. To this end, this study incorporated Bayesian optimisation to efficiently optimise the GA-ANN hyperparameters. The ANN was combined with a GA to mitigate the main drawbacks associated with ANN's, which are the tendency to converge on a local optimum, failing to converge and long computational times. The GA was used to optimise the ANN weights before ANN training commenced to allow for random exploration of the loss surface and to speed up training times enabling more architectures to be explored. A complete description of GA's, ANN's, BO, and the flowcharts for integrating them can be found in [11].

3 RESULTS AND DISCUSSION

3.1 DoE for Ultrasonic Welding

Figure 2(a) shows the average LSS values for the 27 different processing parameters. Run order 27 with input parameters of 1750 J, 1200 N and 100 µm resulted in the highest LSS of 26 MPa whereas run order 20 with input parameters of 1750 J, 1200 N and 100 µm resulted in the lowest LSS of 2 MPa. A visual quality of the joint was performed and was divided into three categories as shown in Figure 2(b).

Additionally, the GA-ANN model was trained at six random input parameters ranging between the minimum and maximum values. The GA-ANN model was developed with the input parameters and the LSS and joint quality. The ANN model identified the optimised parameters to be 1263 J, 842 N and 106 µm with a LSS of 25.3 MPa. Further experiments were performed with the predicted optimized parameters by ANN. The validation test specimens resulted in a LSS of 24.5±0.3 MPa, with a high repeatability and showing zero defects. Therefore, the ANN model predicted the parameters with an accuracy of 97%.



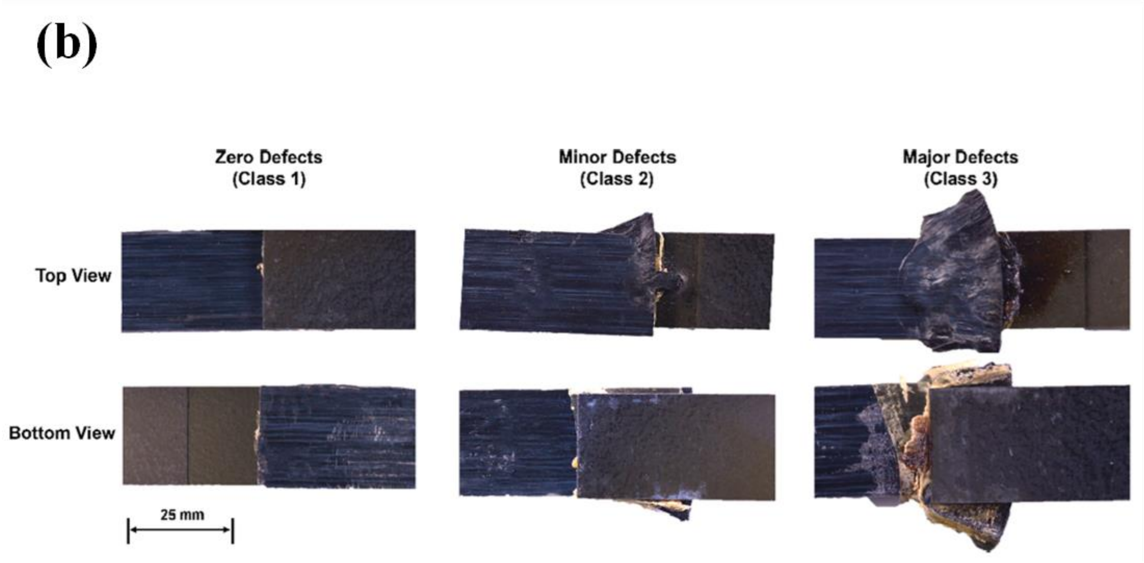


Figure 2: (a) Lap shear strength at different parameters (b) Classification of visual inspection

3.2 Fracture surface analysis

Figure 3 shows the fracture surface analysis performed on the joint interface. Figure 3(a) shows the cross-sectional micrograph of the joint interface. The micrograph shows no signs of degradation or fibre failures at the weld interface. Furthermore, the weld interface for the ultrasonic welded joint specimens had a uniform thickness of ~200 µm. The reduction in the thickness of the PEI film is due to the squeeze flow of the molten energy director as explained in [7]. Figure 3(b), show a fully welded overlap area with PEI resin film push out observed at the overlap edges. Fibre breakages at the central overlap region are observed resulting in an intralaminar failure mode.

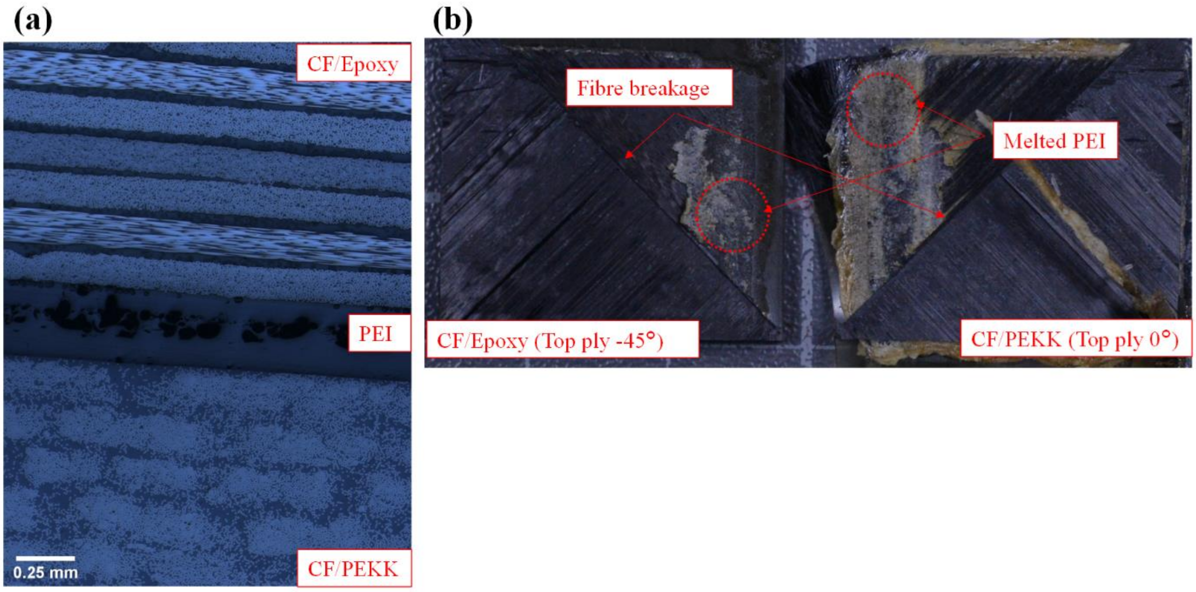


Figure 3: (a) Cross-sectional micrograph of weld interface (b) Visual inspection of fracture surface

4 CONCLUSIONS

A GA-ANN model was created to predict the weld strength and provide the optimised process parameters for the ultrasonic welding of CF/Epoxy to CF/PEKK. The GA-ANN moel predicted with an accuracy of 97% with the predicted optimized strength of 25.31 MPa and a validation strength of 24.46 MPa. The micro-section and the fracture surface of the CF/Epoxy to CF/PEKK showed a strong adhesion between the adherends. The study shows that a GA-ANN model can be used for accurate strength prediction for fusion joining processes, reducing the cost of manufacturing and testing.

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