A SMART INTERFACE FOR MACHINE LEARNING BASED DATA-DRIVEN AUTOMATED FIBRE PLACEMENT

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ABSTRACT

The quality and consistency of the components manufactured by Automated Fibre Placement are dependent on multiple process parameters and their interactions. In order to capture the required data, multiple data collection systems are used which output data in different formats, frequencies and reference systems. This results in a long process with manual steps, which can be error-prone and time consuming, taking as much as 60-70% of the total engineering effort. This study implements a data collection and visualisation platform designed to unify and automate data capture from multiple sources and facilitate the deployment of ML models.

As a demonstration of the platform, multiple components of complex and varying geometry are manufactured at the National Composites Centre, UK. A number of process parameters, including compaction force, surface temperature and lay-up speed, are measured continuously and are used to train and deploy machine learning models with the aid of the smart platform. Data is visualised and a ply-wise neural networks-based model is developed, achieving accuracies of up to $R^2 = 0.80$; demonstrating that the data-driven approach is scalable to complex geometries.

Keywords: AFP, User-interface, Machine-learning, Process-parameters, Data-driven
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1. INTRODUCTION

Automated Fibre Placement (AFP) is an additive manufacturing process in which multiple thin composite tapes are combined within a bespoke robotic head and deposited onto a layup tool in a continuous strip. Material tack and consolidation is aided during deposition; heat is applied to the substrate by an external heat source and compaction force is transmitted through a compaction roller [1-3].

The quality of preforms manufactured by AFP is dependent on a number of process parameters and their interactions, with over 50 independent parameters having influence on AFP quality. This includes; preform temperature, consolidation force, feed rate, lay-up speed and material type [4-5]. Selecting the right combination of process variables is key, with sub-optimal selections leading to delamination or voids, as has been shown by a number of studies [6-8]. For example, it has been shown that poor temperature control can adversely affect layer-to-layer adhesion, resulting in structural defects [2,9].

A deeper understanding of process variables, and their interactions and influences would improve the quality and optimisation of the AFP process [8]. However, physics-based modelling of AFP can be computationally costly due to the complexity of the process and such models have typically been limited in scope and application [10]. As a result, component development tends to be iterative; process parameters are fine-tuned at each iteration until the desired quality is achieved. Development cycles can therefore involve high costs, in terms of both material and time, without a guaranteed optimal solution.

The drive for more consistent high quality components has led to increasingly sophisticated methods [4]. Capable of handling large amounts of data and high dimensionality for a relatively low computational cost, Machine Learning (ML) has been increasingly utilised as a solution to complex, multi-dimensional problems. These methods have the potential to reduce the length of the development cycle and improve the accessibility of AFP as a manufacturing process [10-11]. ML models have previously been deployed to solve a number of complex manufacturing challenges, involving optimisation, control and troubleshooting. This is partially due to the recent availability of large amounts of complex data, and the increased power and usability of ML tools [11].

ML models have also been used in automated composite manufacturing for applications such as design optimisation, performance prediction and manufacturing quality assurance [5,10,12]. Recently, a data-driven approach to ML models for AFP has been successful in predicting selected quality metrics. Initial results on flat, unidirectional preforms show that collecting and transforming data to train predictive ML models can generate highly accurate predictions of mechanical properties such as elastic modulus and Inter-Laminar Shear Stress (ILSS) [4,13].

Despite positive results, predicting and maintaining a consistent output quality in this way remains a time-consuming multi-step process, often involving multiple data collection systems which output data in different formats, frequencies and reference systems. Manual steps are also required to handle this data which can be error-prone, time consuming and lack repeatability. In addition, AFP tends to be used to manufacture highly complex 3D components which are challenging to manufacture by other processes [6]. This introduces a number of complexities which are challenging to model, as both quality metrics and input data can be highly varied and location specific. Steering defects can also be introduced, due to the conflicting requirements of defining a geodesic steering path without straying from design limits. Depositing material in a non-geodesic path leads to buckling of the inner tow edge, which is a common issue with components such as aircraft fuselages [8].

In order for ML modelling to become more widely utilised for AFP process optimisation, data collection and processing methods must become more efficient and accessible. This study utilises a smart platform to unify and automate data capture from multiple sources and facilitate the storage and deployment of ML models. The MAIO platform, an industrial artificial intelligence and data platform developed by Smartia, can be used to:

- Trigger or stop automated data gathering during a manufacturing activity
- Visualise and analyse data from different data sources and manufacturing activities
- Deploy and manage predictive ML models

1.1 Aims and audience

This study aims to demonstrate progress towards the challenge of streamlining the data driven approach, and to show how ML modelling can be used to predict quality of AFP-manufactured complex 3D components.

The first objective is to demonstrate the use of an industrial intelligence platform, MAIO, to capture and manage process data from multiple sources during the manufacture of complex 3D preforms. This will result in time-savings to the data-driven approach by reducing the number of input data systems and hence the number of manual steps involved

The second objective is to use a Design of Experiments (DoE) approach to train and develop an intelligent predictive ML model on data acquired from complex 3D preforms. This model should be capable of predicting an output quality metric for different process variable combinations on a multidirectional 3D preform. This would determine the applicability of the data-driven ML-based predictive approach to increasingly complex geometries.

The intended audience of this study includes industrial and academic manufacturing research engineers. Some knowledge of automated manufacturing processes is required, along with basic knowledge of the AFP process; readers without such background are directed to Lukaszewicz et al. [1].

2. METHODOLOGY

2.1 Materials and output

Preform thickness can be used as a measure of consolidation degree. Consolidation is known to significantly influence the formation of defects during cure or infusion, and is dependent on process inputs [14]. Thickness can also be measured locally on a ply-level to a high degree of accuracy, and a consistent nominal ply thickness is typically required my manufacturers. Ply thickness was therefore chosen as the quality metric for this study.

Deposition was carried out by a Coriolis Composites robotic AFP machine, capable of laying up to eight, 6.35 mm tapes at a nominal maximum speed of 1000 mm/s. The chosen material was bindered dry fibre, as thickness can be directly related to fibre volume fraction (Vf). The deposition tool was designed with multiple complex features and radii typically present in AFP-manufactured components, and is shown in Figure 1. The heat source was a head-mounted diode laser, with a maximum power of 6kW.

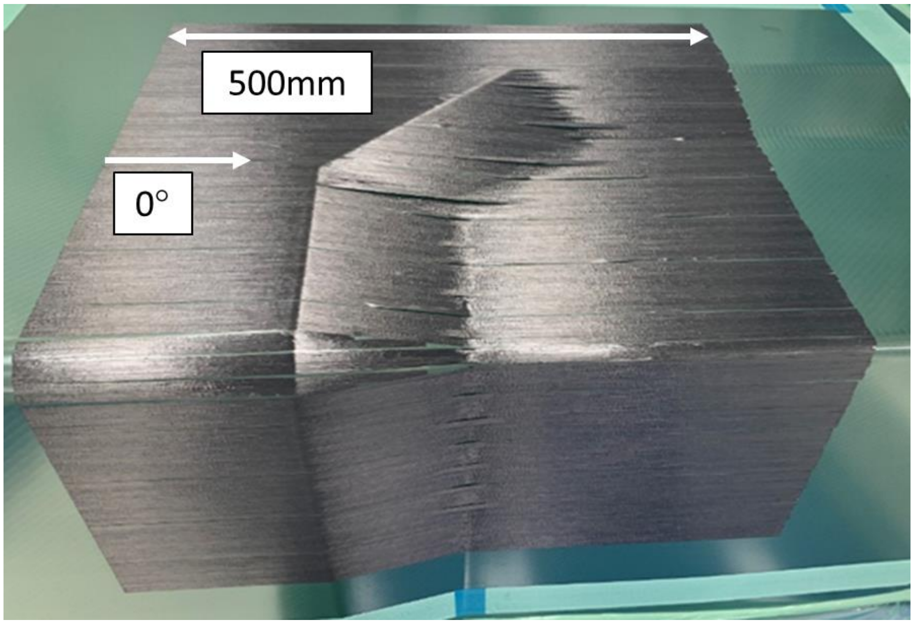


Figure 1. Lay-up tool, including fibre orientation convention, with associated features and internal radii

2.2 Design of Experiments

A DoE approach was implemented to define key control parameters as inputs to the training data [15]. The chosen control variables were:

- *Programmed heater power (3 distinct levels)*
- *Programmed compaction force (4 distinct levels)*
- *Programmed layup speed (2 distinct levels)*

These variables have been shown in previous studies to have significant effect on laminate quality [4,16-17]. The *ply number* is also considered a control variable in the DoE, as ply number intuitively impacts the output variable of preform thickness.

In total, 12 preforms of 8 plies each were manufactured in a quasi-isotropic layup sequence, allowing for a half-factorial DoE. *Programmed layup speed* was defined as a modifier applied to the maximum speed allowable at each point, defined in the layup program. Due to the complex nature of the component, a wide range of speeds were already present in the unmodified layup program. It was therefore decided to prioritise the remaining control variables in a full-factorial

DoE, while randomly distributing a modifier for *programmed layup speed*. The values for each process variable were chosen based on current process knowledge and are shown in Appendix A. The DoE was randomly distributed throughout the 12 preforms in order to reduce bias. The first ply was excluded from analysis in this study, as ply 1 parameters were necessarily maintained constant in each preform in order to maintain the necessary adhesion to the layup tool.

2.3 Data capture

The true value of process parameters can vary significantly from the set values listed in the DoE [8]. Furthermore, process parameters can experience significant intra-course variation due to external influences such as variations in tool geometry, AFP head angle, heating and compaction systems, and acceleration. It is therefore key to capture data with a high accuracy and frequency.

Data was captured from five different sources prior to pre-processing for modelling; environmental data, surface temperature data, machine sensor data, simulated machine TCP position and preform thickness data. In total over 20 parameters were recorded during the study. Preform surface temperature data was measured at the roller nip-point by the head-mounted thermal camera, shown in Figure 2. The MAIO platform was used to capture and store the thermal data as individual images at 30Hz. Temperature data capture was triggered by a command signal from the Coriolis AFP machine at the start of each course.

After each ply was laid, localised thickness data for the entire ply was measured using a Hexagon portable laser scanner measurement arm with an approximate accuracy of 100µm and a point density of up to 10 points per mm. The remaining environmental, machine sensor and TCP position data was captured using the Coriolis AFP machine and a controller emulator, ‘Simureal’. It was then uploaded to MAIO as a .csv file before the data pre-processing phase.

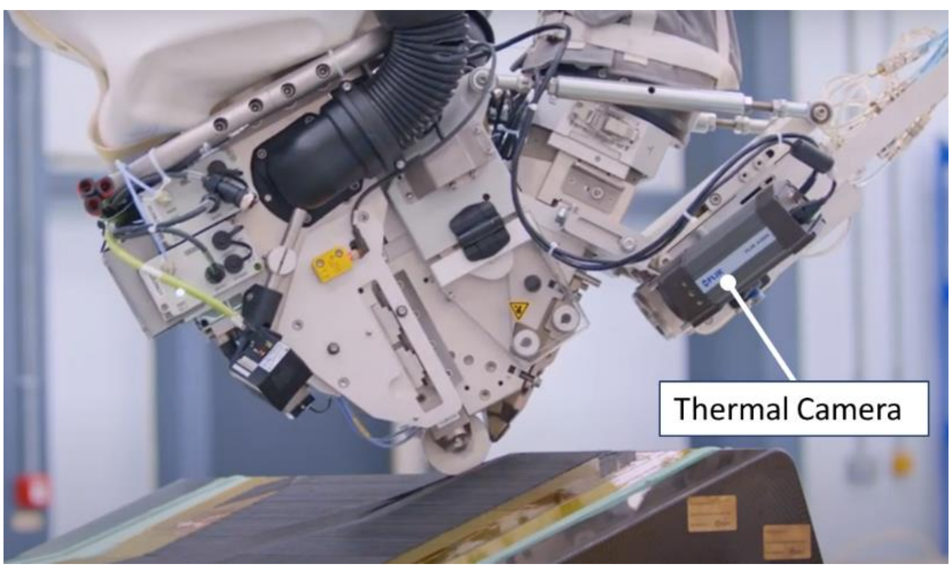


Figure 2. Thermal camera mounting and deposition tool

2.4 Data pre-processing

Before ML modelling can be applied, captured data must be formatted and contextualised so that each measured output can be directly linked to input parameters. This step can represent a significant challenge, and previous experience shows that this step can take up to 70% of the total engineering effort [18].

Pre-processing was carried out using tailored classes and functions in the Python programming language. Data was extracted from each data capture system and conditioned into a standardised format. For example, each thermal image was reduced to digitised data points along a line at the identified roller nip point. Data from each source was then contextualised in order to translate each measured data point into to localised Cartesian position on the preform. A uniform grid was then defined across each ply, and the contextualised datasets for each capture system were interpolated at each node to produce the aligned dataset for statistical modelling. The chosen grid size for this study was 5mm x 6.35mm (1 AFP tow width).

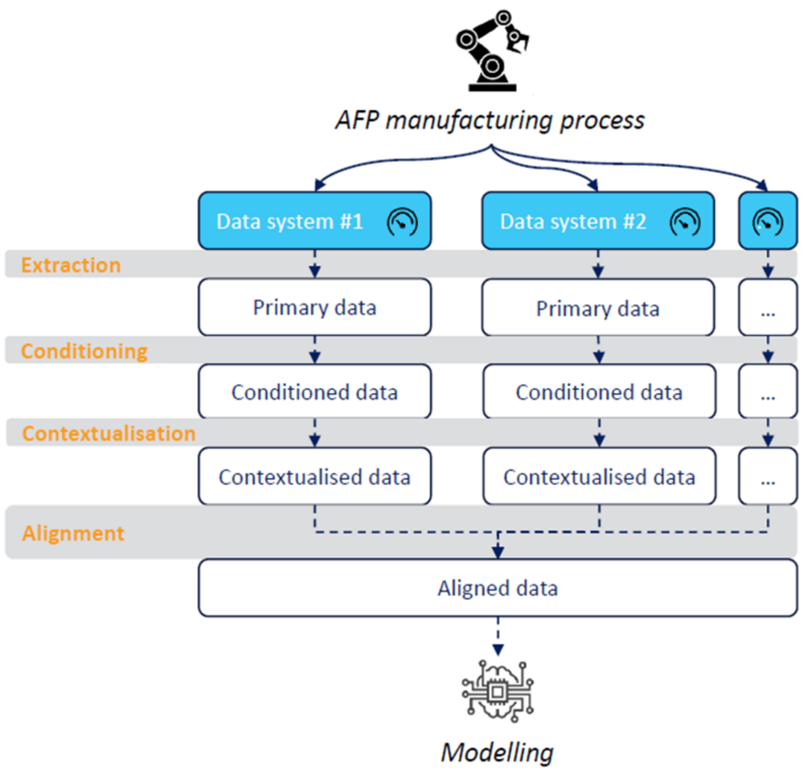


Figure 3. Pre-processing steps to prepare data to be used in ML modelling

2.5 Machine Learning model

ML models were developed using the model development framework shown in Figure 4. For this study, a simplified model was used, taking the eight most significant process variables. The input variables were chosen based on process knowledge and statistical methods to rule out independence from the output variable. The chosen parameters were; *measured compaction force, measured creel humidity*, *measured creel temperature*, *simulated layup speed*, *measured surface* *temperature* and *tool X*, *Y* and *Z coordinates* separately. For these eight parameters, aligned data from all preforms was combined and cleaned.

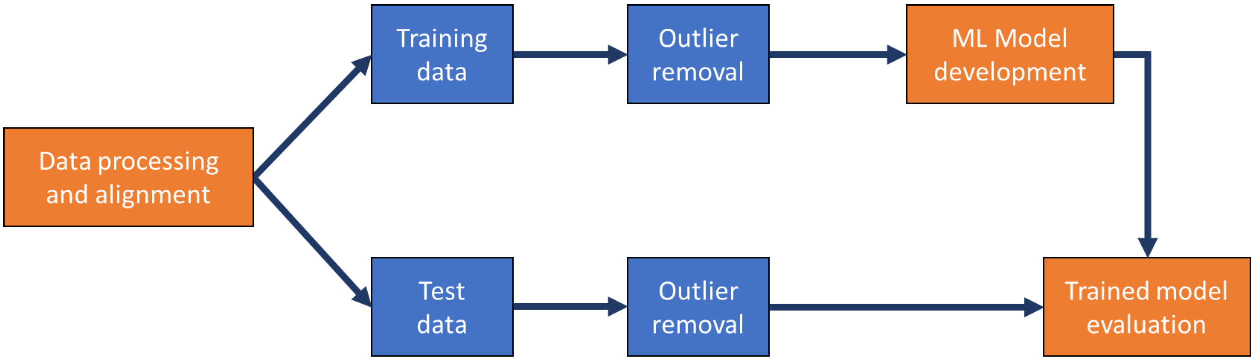


Figure 4. Simplified model development steps

Cross validation was used to validate the model, shown in Figure 4. The dataset was divided into two sets: training and test data. Models were developed using the training data and evaluated using the test data set. A randomised 70/30 train/test split was conducted for each model, and standardised inputs were used to reduce bias. Outliers representing values more than three standard deviations from the mean were then removed from all variables.

To evaluate the model, Mean Square Error (MSE) was calculated using Equation 1, where N , x_i, $\hat{x}_i$ denotes the number of samples, actual value of the sample and the predicted value of the sample respectively [6]. The coefficient of determination, R-squared (R^2), was also calculated. R^2 represents the proportion of the output variance that is predictable from the input features, and is comparable only between datasets of the same scale and size.

$$MSE = \frac{1}{N} \sum_{j=1}^{N} (x_i - \hat{x}_i)^2 \qquad [1]$$

3. RESULTS AND DISCUSSION

3.1 Data visualisation

In Figure 5, an example of course and ply specific data of one ply; preform P8, ply 4, has been visualised for qualitative analysis. As should be expected, lay-up speed is reduced in regions of complex geometry and the measured thickness is higher in concave regions due to bridging (Figure 5d). Figure 5 also shows that process variables differ greatly from programmed values in Appendix A, with Figure 5c showing a variation in compaction force between 375 N and 575 N (i.e. 35% variation).

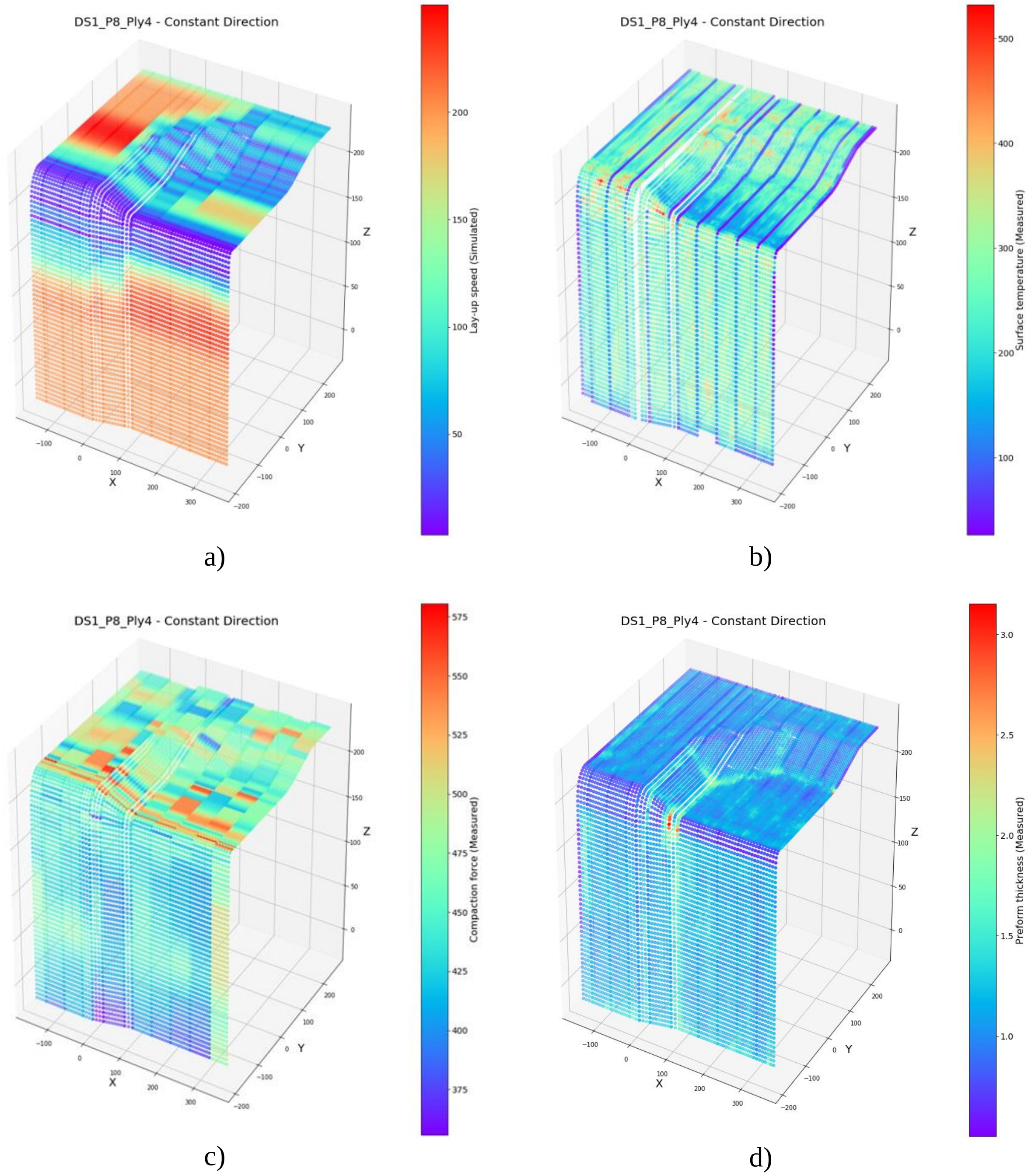


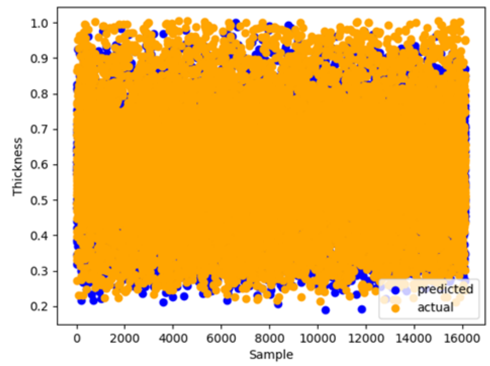
Figure 5. Process variable plots for preform 8, ply 4:
a) Simulated lay-up speed (mm/s), b) Measured surface temperature (°C), c) Measured compaction force (N), d) Measured preform thickness (mm)

3.2 ML model deployment

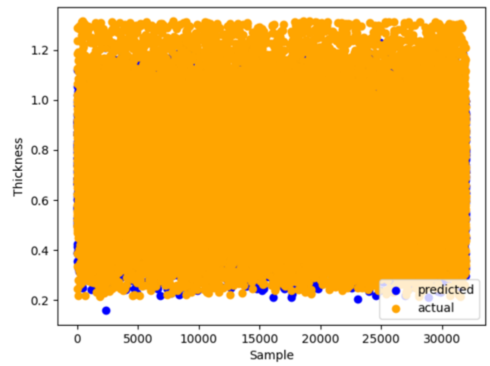
A Neural Network (NN) modelling approach was considered for this study. NNs consist of layered computational nodes and connections. These nodes each perform simple numerical operations, and the results are transferred to the next layer of nodes. Outputs are finally weighted to tune the NN output variable. NNs optimise by inputting multiple test cases and adjusting the weighing parameters to minimise error and achieve the target output value [10].

A deep neural network model was utilised, with 2 hidden layers and leaky-ReLU activation functions to capture the nonlinearity of the data. The NN architecture was selected after training with various values hyperparameters and the values corresponding to the lowest MSE and highest R^2 were maintained. Initial results using the NN showed that ply number had an overwhelming influence on the output variable; the model was able to accurately predict output thickness using only ply number and an average ply thickness. This presented a challenge in that it was therefore difficult to understand the impact of process variables on the result, and also to assess local thickness variations.

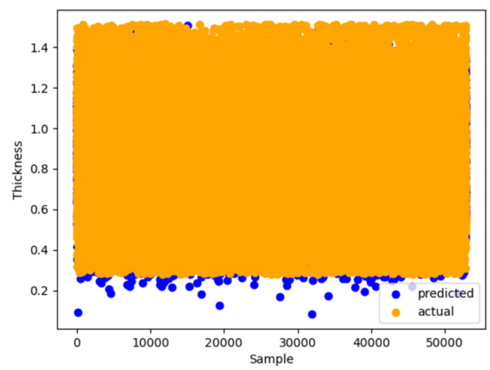
It was therefore decided to develop separate models for each ply in the lay-up sequence (plies 2-8), with identical model parameters and training iterations used for all plies. Figure 6 shows test data values overlayed onto predicted thickness values for plies 2-8. In general, there is a slight tendency to predict lower thickness values, below 0.3mm in the case of plies 4 and 5. This is most noticeable in plies 3-5, which indicates that a key variable could be missing from the inputs. Underprediction could be improved by through the gradual introduction of additional data sources to the model, until underprediction is no longer consistently observed. Figure 7, scatter graphs of predicted vs actual values for the test data, shows that, despite this underprediction, predicted values approximately follow an x=y trendline, with plies 2 and 3 experiencing more variation.



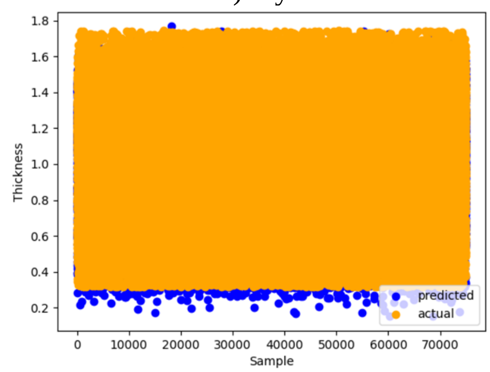
a) Ply 2



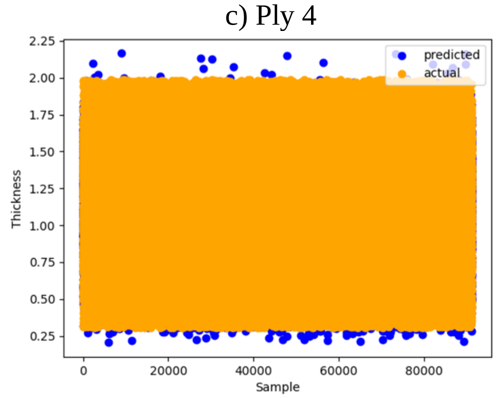
b) Ply 3



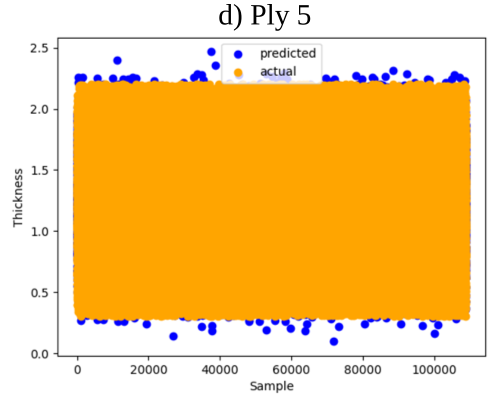
c) Ply 4



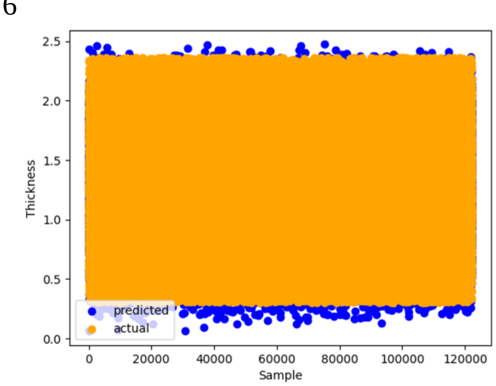
d) Ply 5



e) Ply 6

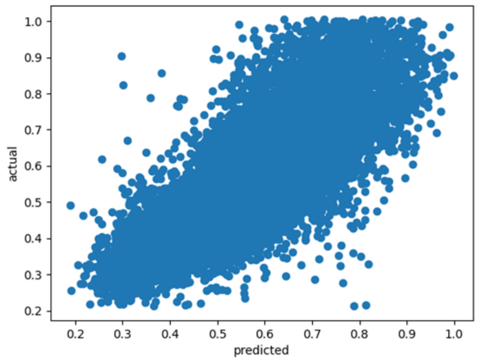


f) Ply 7

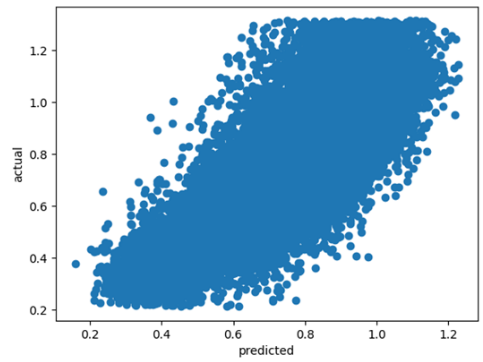


g) Ply 8

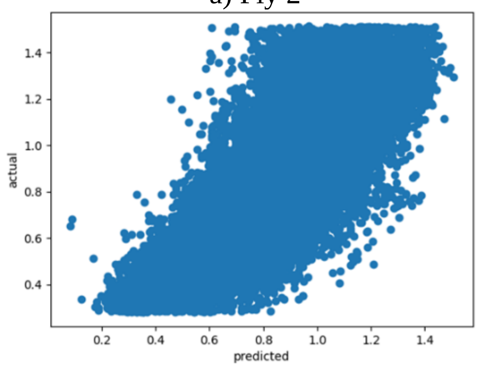
Figure 6. Plots of every thickness data point from the test dataset overlayed onto the equivalent predicted values from the model. a) – g) represents plies 2 - 8



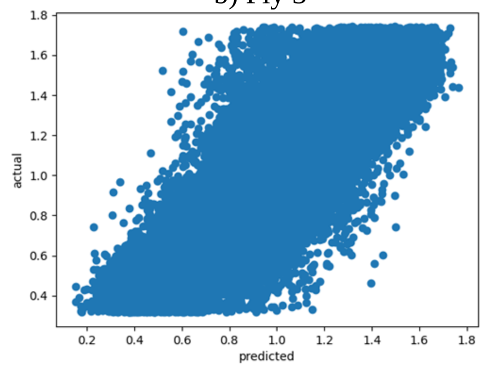
a) Ply 2



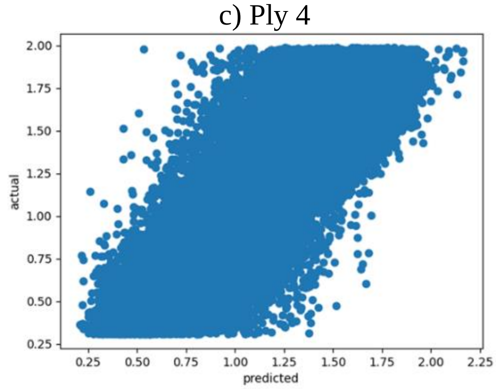
b) Ply 3



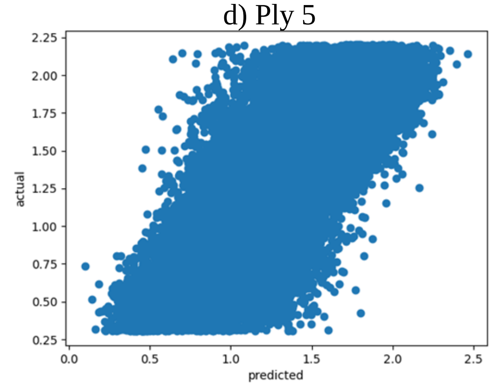
c) Ply 4



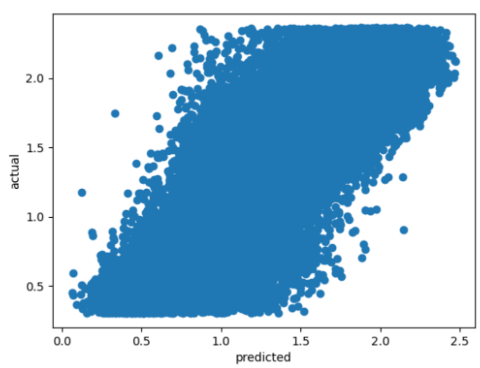
d) Ply 5



e) Ply 6



f) Ply 7



g) Ply 8

Figure 7. Scatter plots of every thickness data point in mm from the test dataset (y) vs. equivalent predicted values from the model (x). a) – g) represents plies 2 - 8

A summary of the evaluation metrics for each ply is shown in Table 1. R^2 values are in the region of 0.61 – 0.80, indicating that the NN models can explain up to 80 % of the variation in output. The methods outlined in Section 2 aim to capture as much process data as possible; however, thickness cannot be perfectly predicted, and an upper limit exists for any ML tool. This is due to randomness present in the AFP process arising from material and process variations beyond those measured. R^2 could be further improved through hyperparameter tuning but the improvements are expected to be incremental. Similar projects have also improved their error through the use of inverse modelling [6] or expanding the sample size through virtual sampling [4].

The variation in R^2 present in Table 1 suggests that prediction accuracy increases with ply number, with ply 2 experiencing the lowest R^2. This trend is also shown to some extent in Figure 7, where plies 2 and 3 appear to be more variable than subsequent plies. The diminishing impact of random variations in lay-up condition as ply number and preform thickness increases could explain the discrepancy. Accuracies could be improved through the introduction of further data sources, additional to the eight chosen for the initial model. Increasing the volume of input data and investigating the advanced modelling methods listed above could also improve the result. The presence and variation of steering-induced defects has also not been considered in detail, and these will have a significant localised effect on thickness.

These results demonstrate that it is possible to accurately predict preform thickness based on captured AFP process data, and that the data-driven approach to model development is scalable to complex 3D components

Table 1. Predictive performance of the per-ply models for plies 2-7

Ply number	Orientation	MSE	R^2
2	-45°	0.00872	0.605
3	45°	0.01499	0.664
4	90°	0.01795	0.739
5	90°	0.02163	0.782
6	45°	0.03141	0.778
7	-45°	0.04303	0.777
8	0°	0.04527	0.801

4. CONCLUSIONS AND FURTHER WORK

This study has produced accurate predictions of an output quality metric, preform thickness, based on AFP process data captured during deposition of complex 3D components using a data-driven approach. Comprehensive AFP process data has been captured using the MAIO industrial intelligence platform and additional data sources, in order to train and validate ML models. A total of twelve, quasi-isotropic preforms of eight plies each were deposited onto a tool with complex features. Data visualisation highlighted the variability of process variables from their set values and identified artifacts such as bridging.

ML models developed in this study have shown promise in predicting output quality based on training data. Ply-wise models based on neural networks have successfully predicted preform thickness using a randomised train-test split, to a maximum R^2 of 0.80. R^2 values were found to increase with ply number, magnifying the impact of small lay-up variations at lower preform thicknesses. Accuracy could be improved in further iterations through model optimisation techniques.

Further work will increase the number of data sources captured in real-time by MAIO, resulting in time-savings during the lengthy data processing stage. The current models will be further optimised and validated using new data captured using the same methods, materials and tool. Conclusions will also be verified against models based on data captured at the NRC Aerospace, Canada, using a different AFP machine, tool and material system. This would investigate the transferability of the data driven methodology to generalised AFP manufacture.

5. ACKNOWLEGEMENTS

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7. APPENDIX A

Table 2. Design of experiments set (target) parameter values.
A1, Preform ID; A2, Ply number (8 levels); A3, Temperature (3 levels, °C); A4, Compaction force (4 levels, N); A5, Deposition speed modifier (2 levels)

A1	A2	A3	A4	A5	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5
P1	1	190	300	20%	P5	1	190	300	50%	P9	1	190	300	50%
	2	190	150	50%		2	260	300	100%		2	260	450	100%
	3	290	300	20%		3	260	150	100%		3	260	300	100%
	4	190	100	50%		4	230	300	100%		4	190	300	50%
	5	230	100	20%		5	260	150	100%		5	260	450	100%
	6	230	150	20%		6	230	100	50%		6	230	300	100%
	7	190	300	50%		7	260	300	50%		7	260	450	50%
	8	260	300	50%		8	190	300	50%		8	260	100	100%
P2	1	190	300	20%	P6	1	190	300	50%	P10	1	190	450	50%
	2	230	150	20%		2	230	300	50%		2	230	450	50%
	3	230	450	20%		3	190	150	50%		3	230	300	100%
	4	190	100	100%		4	230	150	50%		4	260	100	100%
	5	190	300	50%		5	230	150	100%		5	190	450	100%
	6	230	100	20%		6	230	450	100%		6	260	150	100%
	7	230	100	20%		7	260	150	100%		7	230	150	50%
	8	260	150	50%		8	190	450	50%		8	190	100	50%
P3	1	190	300	20%	P7	1	190	300	50%	P11	1	190	150	50%
	2	260	150	100%		2	230	100	20%		2	190	300	50%
	3	230	150	50%		3	260	100	100%		3	260	450	100%
	4	190	150	50%		4	230	100	100%		4	260	150	100%
	5	190	100	50%		5	190	150	50%		5	260	300	100%
	6	190	300	50%		6	260	450	100%		6	190	150	100%
	7	190	450	50%		7	230	300	100%		7	190	100	50%
	8	260	150	100%		8	230	450	100%		8	230	300	100%
P4	1	190	300	20%	P8	1	190	300	50%	P12	1	190	300	50%
	2	190	100	50%		2	260	100	50%		2	190	450	100%
	3	190	300	50%		3	190	450	50%		3	190	100	50%
	4	260	450	100%		4	190	450	50%		4	230	450	100%
	5	230	450	100%		5	260	100	100%		5	230	300	50%
	6	190	100	50%		6	190	450	50%		6	260	300	100%
	7	190	150	50%		7	260	100	50%		7	230	450	100%
	8	230	100	50%		8	260	450	100%		8	230	150	100%