# A SMART INTERFACE FOR AUTOMATED FIBRE PLACEMENT

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## ABSTRACT

The quality and consistency of components produced 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 typically 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. This study implements a data collection and visualisation platform designed to unify and automate data capture from multiple sources and facilitate the deployment of process models. As a demonstration of the platform, multiple complex and multidirectional components 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 using the smart platform. Process variable distributions are visualised, and the data is processed into datasets which can be used to train process models.

## 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. It also visualises and processes the data into a format conducive to statistical and ML modelling. The MAIO platform, an industrial artificial intelligence and data platform developed by Smartia, can be used to; trigger in-process data gathering, analyse data from multiple sources, and process data to feed into ML models.

# 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 is directly related to fibre volume fraction ($V_f$). 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.

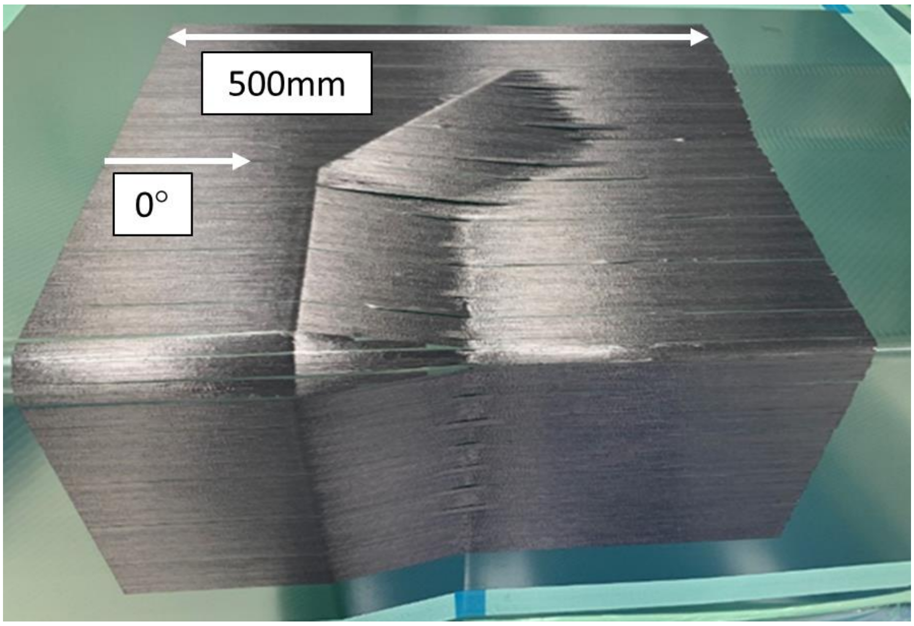


Figure 1. Lay-up tool, including fibre orientation convention, with associated features and internal radii

## 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. Process variable combinations were distributed throughout the 12 preforms in order to reduce potential biases. 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.

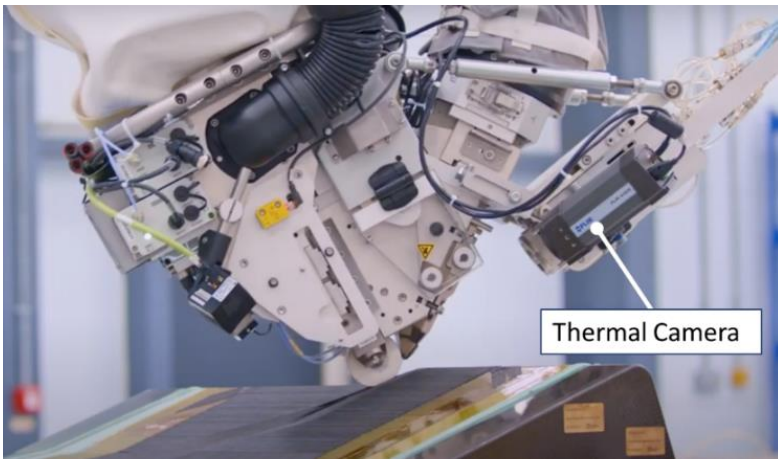


Figure 2. Thermal camera mounting and deposition tool

### 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 a large portion of the total engineering effort. 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).

# 3. RESULTS AND DISCUSSION

## 3.1 Data visualisation

Figure 5 shows an example of process data from one 90° ply; preform P8, ply 4, with lay-up in the positive *Y* direction. Measured values of the three control variables are visualised; lay-up speed, compaction force and nip-point surface temperature, along with the output variable, preform thickness.

Figure 5a shows the lay-up speed distribution over the ply. Speed is reduced in regions of complex geometry due to limitations in the machine's motors and controllers. Lower speeds have been associated with improved quality due to greater contact time and increased heat flow across the material interface [8], which could contribute towards a reduced thickness at the 90° bend region. Figure 5c shows the distribution of compaction force across the ply. Compaction force is set at 450N. However, the measured force varies between 375N and 575N, a 35% variation across the ply. This discrepancy between set and measured compaction force is also noted in [8], and demonstrates the necessity for measuring compaction force continuously in order to accurately define its effect on thickness.

Figure 5b shows the nip-point temperature distribution. Temperature is controlled by a power law, designed to keep the nip-pint temperature constant with changing speed. There are strips of low temperature at the boundaries of each course, and this indicates that the laser may not be heating the nip-point evenly. Within these boundaries, the temperature mostly varies between 200°C and 350°C. Areas of significantly increased temperature (up to 500°C) are observed in the 90° and smaller bend regions. These localised hot spots and are likely caused by physical changes such as temporary changes in the laser's heating distance or power law limitations at low speeds.

Finally, figure 5d shows the distribution of measured thickness across the ply. Geometrical features can be observed, such as thickness increases at the concave regions cause by bridging. A reduction in thickness is also observed at the 90° bend region, aligning with regions of reduced speed and increased temperature. ML process models will be trained using this data to investigate these relationships and generate thickness predictions.

# 4. CONCLUSIONS AND FURTHER WORK

Comprehensive AFP process data has been captured using the MAIO industrial intelligence platform and additional data sources, in order to develop datasets which can be used to train process models. A total of twelve, quasi-isotropic preforms of eight plies each were deposited onto a tool with complex features. Initial visualisation highlighted the variability of process variables from their set values, demonstrating the need for real-time data capture. Layup features such as bridging were also identified and in further work, this process data will be used to develop process models to understand and predict preform thickness based on input variables.

Conclusions drawn from these models will also be verified against models trained using data captured at the NRC Aerospace, Canada, using a different AFP machine, tool and material system. This will investigate the transferability of the data driven methodology to generalised AFP manufacture.

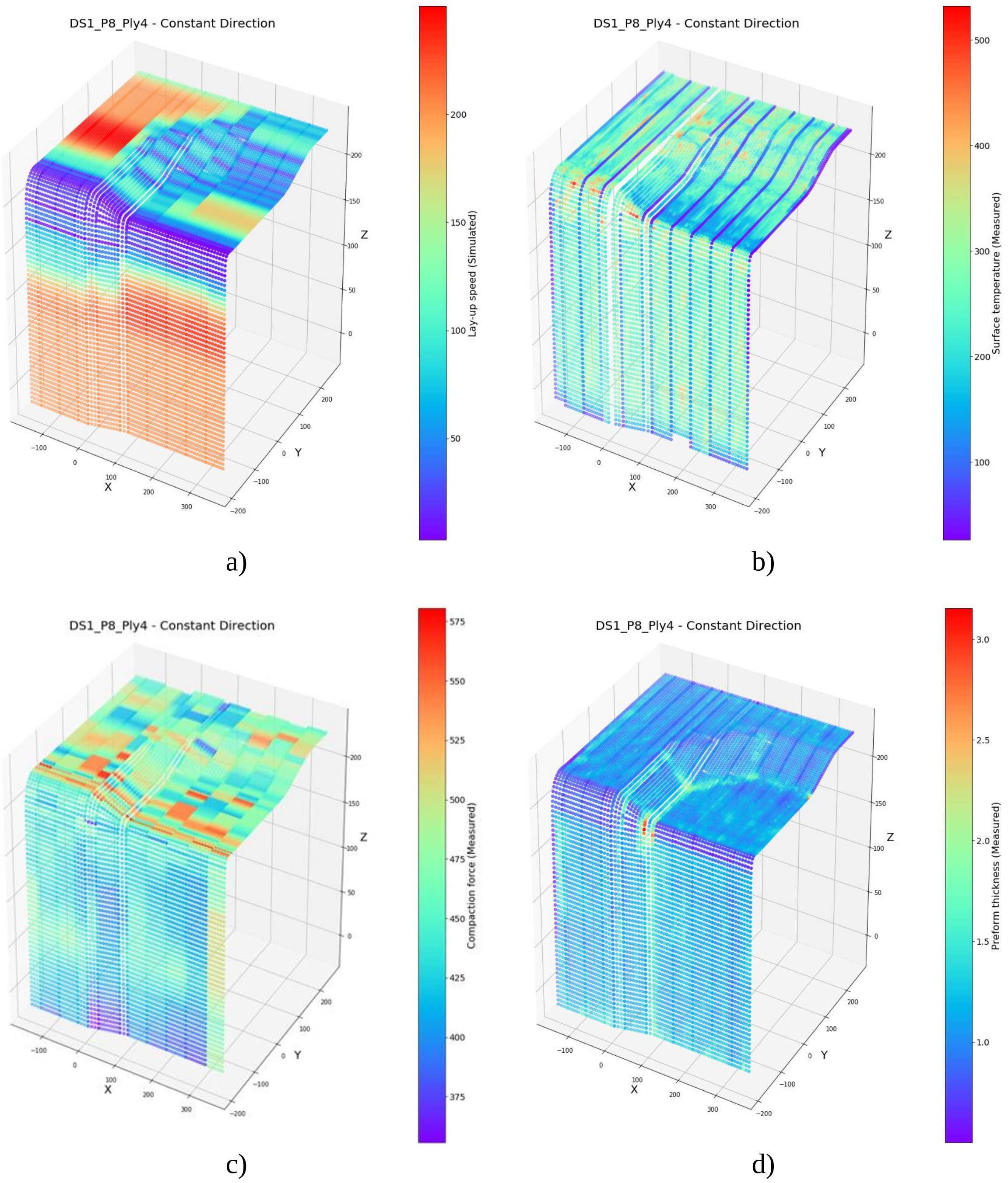


Figure 3. Process variable plots for preform 8, ply 4:
a) Simulated lay-up speed (mm/s), b) Measured surface temperature (°C), c) Measured compaction force (N), d) Measured preform thickness (mm)

## 5. ACKNOWLEGEMENTS

This study is supported by the *Data Driven Processing Towards Affordable Automated Composite Manufacturing* project, Innovate UK. This work is also supported by the Engineering and Physical Sciences Research Council through the EPSRC Centre for Doctoral Training in Composites Manufacture (grant: EP/L015102/1) and The Future Composites Manufacturing Hub (grant: EP/P006701/1). The authors acknowledge the National Composites Centre and Bristol Composites Institute (ACCIS) for their support of this research. All data necessary to reproduce the results and support the conclusions can be accessed through the named corresponding author. The author would also like to thank Philippe Monnot for his significant contributions towards the projects and methods used within.

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# 7. APPENDIX A

Table 1. 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% |