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## Machine Learning Approach for Optimization of Automated Fiber Placement Processes

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### Abstract

Automated Fiber Placement (AFP) processes are commonly deployed in manufacturing of lightweight structures made of carbon fibre reinforced polymer. In general, AFP is connected to individual manufacturing knowledge during process planning and time consuming manual quality inspections. In both cases, automatic solutions provide a high economic potential. Therefore, a machine learning approach for planning, optimizing and inspection of AFP processes is presented. Process data from planning, CNC and online process monitoring is aggregated for the documentation of the part specific manufacturing history and the automated generation of manufacturing knowledge. Within this approach a complete automation of data capturing, data storing, modeling and optimizing is achieved.

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### 1. Introduction

#### 1.1. Motivation

Especially in aerospace applications, lightweight structures are becoming increasingly important aiming to reduce the fuel consumption. Therefore, modern wide-body aircrafts like Boeing 787 [1] or Airbus 350XWB [2] consist of more than 50% composite materials by weight, especially carbon fiber reinforced plastics (CFRP). Due to the high strength-to-weight ratio compared to conventional aircraft materials, the relative share of structural parts is up to 80% by volume. Such integral constructed parts are characterized by huge dimensions and high unit costs. For this application, the Automated Fiber Placement (AFP) process evolves into one of the leading manufacturing processes in lightweight design. This process combines high productivity with high quality. Within this process, several pre-impregnated carbon fiber slit-tapes are laid-up by a fiber placement head on a tooling surface side-by-

side simultaneously. During the lay-up process, certain defects may occur. They can be divided in four categories:

- Positioning defects (gaps, overlaps, missing tows, twisted tows)
- Bonding defects (bridging, air pockets)
- Contaminations
- Tow defects

Today, AFP processes are distinguished by a high amount of manual interventions in process planning, process and quality assurance (QA). As an example, the quality control during AFP processes is manually done by visual inspection of the operator. In this time, the lay-up process has to be interrupted. The visual inspection and the potential repair process in cases of detected defects are done for every single ply during the AFP process and are therefore very time-consuming.

In the AFP process, pre-impregnated carbon fibers (tows) are placed automatically on a tool surface. Due to recent technological advances in the production technology, increasingly complex parts can be realized. However, this

progress also entails a higher complexity of the tools and tool surfaces. Regardless of existing CAD-CAM applications, the additional high structural requirements for CFRP laminates demand a manual, time-consuming adaptation of the laying paths while adhering to strict design rules. In addition to the selected tow paths, the process parameters have a decisive influence on the laying quality. Inadequately pre-heated tool surfaces or deviating compaction pressure can lead to defects, such as surface-dissolving tows. If existing errors are not detected and corrected, deviations from design and structural requirements of the component occur. As a consequence, the machine operator is responsible for quality assurance, which is related with a time-consuming visual inspection of the individual layers. This approach not only restricts the productivity of the AFP process, but also entails high repair costs for undetected errors, which need to be corrected at a later stage, or in exceptional cases can lead to the rejection of the entire component.

### 1.2. Monitoring and optimization of manufacturing processes

As Soucy showed, a camera system mounted on the fiber placement head can support the operator during machining [3]. This enables the operator to inspect continuously the lay-up of fiber tapes. However, this approach is not corresponding to an online process monitoring, because of the high demands on cognitive abilities of the operator. Today, automated visual monitoring systems are not common due to the high demands on illumination and image analysis [4]. Nevertheless, several visual monitoring approaches were developed. As an example, Miene showed an algorithm for the calculation of the fiber orientation for single rovings during the manufacturing process of carbon fiber reinforced plastics (CFRP) for the prognosis of occurring defects. Disadvantages of this approach are the time-consuming numerical image analysis and the ambient conditions depending reliability [5]. A different approach is the using of laser triangulation sensors for the monitoring of single tows. The monitor system is able to localize the position of the tows by an edge detection [6]. In the field of quality control of fiber-reinforced components the use of ultrasonic probes is prevalent after the manufacturing process [7].

Several machine learning approaches are presented for different manufacturing applications. For metal cutting processes an overview on applied optimization techniques are given in [8] and [9]. In recent research evolutionary optimization algorithms, particularly Genetic Algorithms (GA), Simulated Annealing (SA) and Particle Swarm Optimizing (PSO) are focused [9]. Nevertheless, the correlations between process parameters and their effects are not modelled by these algorithms, because a model for the optimization process was not required in the given application. Therefore, the determined process parameters were only applicable for the given process with a restricted set of boundary conditions. For milling processes, a method based on a support vector machine as a machine learning approach to model the obtained process data was shown. By using a numerical optimization of the model, optimal process parameter could be determined to minimize machining time and satisfy given boundary conditions. Due to the complete automation of data capturing, data storing,

modeling, optimizing and machining, a self-optimizing cutting process was achieved [10] and [11].

### Nomenclature

AFP	Automated Fiber Placement
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CFRP	Carbon Fibre Reinforced Plastics
FPA	Focal Plane Array
IR	Infrared
NC	Numerical Control
$p_c$	Compaction pressure
QA	Quality Assurance
RA	Regression Analysis
SVM	Support Vector Machine
$T_H$	Heater temperature
$v_{AFP}$	Lay-up velocity

## 2. Approach

### 2.1. Idea

The basic idea of the presented approach is a continuous data storage and usage over several steps of the process chain. In the first step, the AFP process is planned by using the currently best known process parameter. In the next step, all relevant information of the planning process is used for the parameterization of the process monitoring system. As an example, the placement path is extended by correlating planned gaps and tolerances. During the manufacturing process, the online monitoring system is able observe the process and to classify detected anomalies based on planning data. In addition, all process information from planning, the machine control and the monitoring system are aggregated in a database. Afterwards, the manufacturing data can be used in two different ways. On the one hand the detected defects and anomalies are visualized during QA to support the operator. On the other hand, the aggregated data is analyzed by machine learning methods for optimization of process parameters of future processes. The described approach is schematically shown in Fig. 1. In the following, the mentioned modules are described in detail.

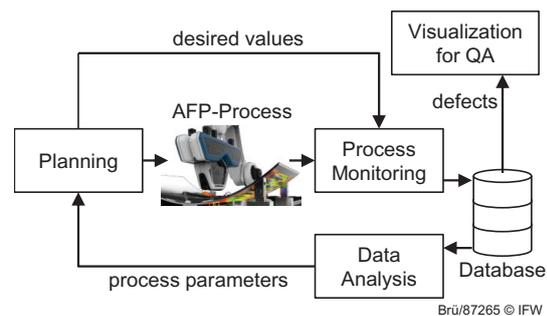


Fig. 1. Approach of data aggregation based process optimization

## 2.2. Planning information

As shown before, all relevant information of the planning process have to be used for the parameterization of the process monitoring system. Due to the fact, that the extension of G code by additional parameters is limited, the process information like position depending thresholds or placement conditions (planar, convex, concave etc.) are written in an XML-file. In addition, a separate parameterization file provides the opportunity to segment the process in a higher level than the original G code. This can be necessary if one planning parameter varies over one NC operation or in case of changing placement situations like different subsoils. An additional reference in G code and the current position are used for synchronization of process and monitoring system. The provided information includes the planned gaps for each tow, the placement velocity, starting and end points, ply orientation and the placement situation on the subsoil like convex or concave surfaces. In addition, further information like program file name, product name and material are provided by the parameterization file.

## 2.3. Thermographic process monitoring

For monitoring of the AFP process, an integrated infrared (IR) camera delivers continuously thermographic pictures to a data unit. The camera, type AT IRS-640, has a resolution of 640 x 480 pixel at 50 Hz based on a focal plane array (FPA) detector with a pixel distance of 17  $\mu\text{m}$  x 17  $\mu\text{m}$ . Temperature measuring range is between -20°C to +150°C with a thermal sensitivity of <50 mK. The camera uses a lens with a focal range of 10 and a horizontal angular aperture of 57°.

An image processing algorithm is able to detect different kinds of defects and to provide quality information in real time. The principle approach of the process monitoring is based on a visible temperature difference between the tows and the tool surface or already deposited tow layers during the depositing process. The material is kept cool within the laying head in order to ensure the desired material properties as well as the processability of the material. In addition, adhesive bonding of the tows in the material supply is also prevented. However, for a good adhesion of the tows on the tool surface, the tows must have a certain stickiness. This is achieved by warming up the tool surface immediately before storing the tows. The resulting temperature difference between the heated substrate and the still cool tows is clearly visible in the thermal image. By consolidating the tows with the tool surface, heat is transferred to the tow. Depending on the laying speed, the adhesion quality and the consolidation pressure, the tow temperature equalizes to the tool temperature.

A distinct visible thermal contrast is present between the freshly deposited tows and the surface of the subsoil (Fig. 2). Using an edge detection algorithm, the edges of the single tows are determined and the positions of the tows are stored continuously in the robot coordinates. Deviations from the nominal positions of the path are recorded online so that path-specific threshold values can be compared with the current values from the process monitoring.

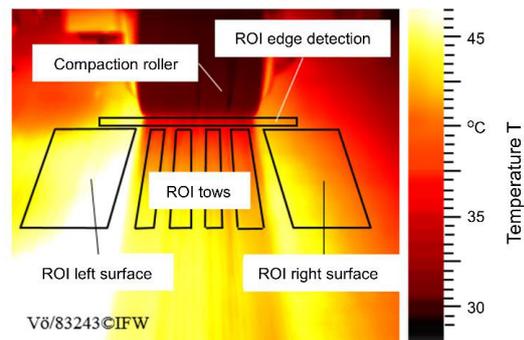


Fig. 2. Regions of interest for the surface inspection by an IR camera

In addition to the localization of the tows, the surface temperature distribution is also monitored and stored. The analysis of occurring temperature anomalies is used for the detection of surface defects, such as poor adhesion of the tows or foreign bodies. The developed algorithm can detect a plurality of defects online like gap deviations, overlaps, twisted tows, bridging and foreign objects. The applied thermographic monitoring system is described in detail in [12].

## 2.4. Process data aggregation

A suitable data exchange between the monitoring system and the data aggregation module is necessary for the efficient aggregation of process information. The applied network protocol is based on the high-performance asynchronous messaging library Zero MQ [13]. For the data exchange in AFP processes a standardized format was defined. By using this format, the process information is provided in a very efficient way including the detected gap deviations, temperatures and defects together with machine data and reference to planned placement settings.

For the aggregation of the received process data, the high throughput, write speed optimized database Cassandra is used [14]. Cassandra is designed to scale horizontally and allows adding database nodes to increase the amount of data that can be handled. Therefore, the setup can be used for a large number of placement units in a large scale production. Through this setup and the connection between the placement unit and placement data base, a complete automation of data capturing, data storing, modeling, optimizing and placement process was achieved.

## 3. Experimental setup

The experimental manufacturing cell is based on a commercial six axis industrial robot Kuka KR 350. The end effector is guiding the placement head for the AFP process. The AFP head is designed for placing four 6.35 mm wide tows.

As shown in Fig. 3, the described thermographic process monitoring system (sec. 2.3) is mounted on the laying head. In addition, further sensors are integrated for monitoring of temperature, humidity and tow tension together with approximating the amount of the material left in the supply

unit. The temperature and humidity are measured and recorded inside the laying head in the material supply unit to determine the ambient conditions in close vicinity to the nip point during placement process. Pyrometers are used for measuring the temperature of the tow inside the laying head and for the temperature control of the heating unit. Furthermore, one pyrometer measures the temperature of the mold respectively of the placed tows. Another pyrometer monitors the temperature directly in front of the compaction roller. Finally, pressure sensors measure the tow tension and ultrasonic distance sensors detect the material in the supply unit. The applied placement unit system is described in detail in [15].



Fig. 3. Laying head with integrated IR camera

#### 4. Automated data analysis and machine learning

The shown approach is examined in an experimental scenario. Focus of these experiments is the correlation between process parameters and thermal behavior during lay-up. The tows are placed on a planar and thermal isolated aluminum tooling. The experimental design is summarized in Table 1. The experiments are described in detail in [16].

Table 1. Summary of experimental design.

Parameter	Symbol	Levels	Unit
Lay-up velocity	$v_{AFP}$	0.1, 0.2, 0.3	m/s
Heater temperature	$T_H$	30, 40, 50	°C
Compaction pressure	$p_c$	0.56, 1.06, 1.67	MPa

During the experiments, 85 different process values are continuously stored in the database. The main values are end-effector positions and velocities, local temperatures, compaction pressures and detected gaps. For each experiment approximately 4,000 datasets are aggregated. A total of 84,000 data sets are available for the following data analysis.

In the first step of data analysis, the aggregated data is filtered depending on the case of application. For the identification of relevant information, the filtering criteria are exemplary the placement system, the tow material or the heater temperature. In the next step, the data is divided in dependent (output) variables  $y_i$  and explanatory (input) variables  $x_{i,p}$

Dependent variables are exemplary surface temperatures, gap deviation or the occurrence of twisting and overlapping tows. Examples for explanatory variables are the placement velocity, the compaction force or the curve radius of the placement path.

In the main step of the data analysis, each dependent variable is analyzed by using linear regression respectively multiple linear regression. Therefore, a common Cholesky algorithm is used for the calculation of the decomposition matrix. In an initial data analysis, the coefficient of determination  $R^2$  is used for the identification of unknown significant correlations. Measurement data and an automated generated model of temperature behavior in compaction zone depending on the placement velocity and the compaction pressure are shown in Fig. 4.

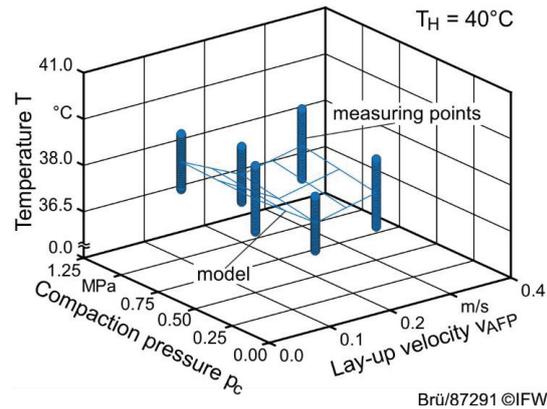


Fig. 4. Aggregated process data and predictive model

In the current experiments the regression analysis identifies a correlation between the compaction pressure and the measured temperature in the compaction zone. This leads to an improved adhesion of the tows and an increasing heat transfer from subsoil to tow. This behavior was also identified and examined in detail by classical design of experiments in [16]. At this time, a further examination of detected correlations like clustering of data sets or the consideration of time depending behavior is not realized in an automated way.

The continuous optimization of process parameters respectively process models is a further application of the automated data analysis. In this use case, predefined dependent and explanatory variables are analyzed by regression to update model equations of established correlations. One scenario for this application is the compensation of varying material quality or decreasing precision of manufacturing systems. Therefore, the described automated formulation of correlations between process variables and effects is used. As shown in Fig. 1, the updated parameters are transferred back to process planning.

#### 5. Visualization of defects

The developed evaluation module stores the detected errors in a three-dimensionally resolved production protocol based on XML. In addition to the process documentation, this information is made available for subsequent inspections

within quality control and assurance. For this purpose, the production information is processed, classified and projected onto the virtual component model in a user-friendly manner. The open graphic library OpenTK is used for this visualization. In addition, the user can select individual data points to obtain further local information. In this way, exemplary referenced NC sets, process parameters or thermographic images can be displayed for an individual evaluation (see Fig. 5). By restricting quality control to relevant component areas, the effort and costs for quality assurance can be significantly reduced. This aspect is especially important in aerospace industry, since complex and non-destructive tests of entire components are currently required as non-value-adding process steps.

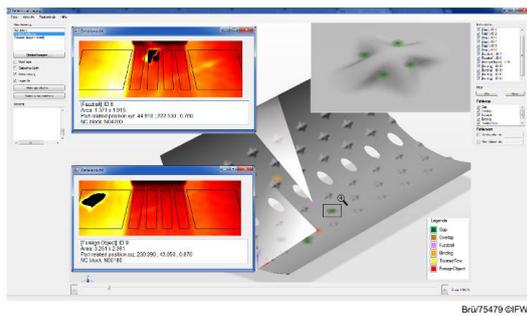


Fig. 5. Visualization of detected and classified manufacturing defects

## 6. Conclusion and outlook

During AFP manufacturing, various process data are generated in different process steps and by different tools like CAM system, CNC controller or process monitoring system. The aggregation of these data provides the opportunity to extract extended knowledge during manufacturing. For this reason, a new method for the automated aggregation and interpretation of AFP process data is shown in this paper. In addition, a new software tool for the visualization of detected process anomalies is presented for the use in the field of QA.

The benefits of the approach were shown for one exemplary process setup with a typical tape material. Like in other manufacturing processes, the applied material and machine has a high influence on the results. Therefore it is necessary to acquire specific data for the automated process characterization. The technical environment, like IR camera system, image processing algorithms, data base and machine learning algorithms, is adaptable for different processes. It is only necessary to parametrize the camera system for the applied material and the monitoring system with specific thresholds. In addition, varying machine specific behavior like decreasing positioning accuracy can be inherently detected for

predictive maintenance by considering data from processes with different materials and molds.

In future, the automated data analysis has to be extended by additional analysis methods like support vector machine (SVM) and automated clustering and filtering of data sets. In addition, results from QA like NDT data have to be matched with planning and process information for increasing modeling quality.

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