A digital twin for composite parts manufacturing

Effects of defects analysis based on manufacturing data

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***Abstract*—The manufacturing of structural parts made from carbon fiber composite materials is a complex process that requires extended quality control. To facilitate better decisions about the mechanical properties of the part and, consequently, the need for re-work, a manufacturing database is proposed that creates a digital twin of the part as manufactured. The main contribution of the paper is to highlight how to merge incoming sensor data into the database and how to use these data to determine the margin of safety for the part. This is demonstrated on the example of an ADMP (automated dry material placement) process during the manufacturing of a section of an aircraft wing lower cover.**

Keywords—digital twin, carbon composite manufacturing, cyber-physical systems, optical surface inspection

I. INTRODUCTION

Structural parts made of carbon fiber reinforced plastics (CFRP) are key components of modern, lightweight airplanes. For obvious reasons high standards in terms of quality have to be met. Due to the complexity of the production process safety margins need to be included in the mechanical design of such parts, which in turn offsets some of the advantages of lightweight components. A better understanding and documentation of the production process will help to keep the safety margins within reasonable ranges and will also enable more efficient defect handling and re-work processes.

This paper presents a method to enable such documentation based on a "manufacturing database" that collects information about the part "as manufactured" in contrast to "as designed" [1]. The method is based on creation of a so called digital twin that consequently enables finite element calculations to assess the properties of each particular part based on how the part was manufactured.

After a review of previous work in section II, section III contains information about the production process as well as defect types and sensor systems used to acquire the necessary data about the part for generating a digital twin. In section IV the structure of the manufacturing database is explained and how data are being collected in real-time during the production process. Results are presented in section V.

II. RELATED WORK

The concept of a digital twin for various products has been proposed in many recent publications [2], [3]. For the aerospace industry, the investment in the infrastructure to realize a digital twin is especially interesting, because costs of the structural parts that are produced are relatively high and monitoring of parts pays off quickly. Furthermore, substantial savings may be achieved due to a reduction in end of line testing [4]. Therefore, the interest in implementation of digital twins is probably highest in the aerospace industries. Different approaches and concepts were recently proposed for digital twins in the aerospace industry [5, 6].

Among concepts related to the internet of things, cyber-physical systems cover the idea of two-fold architectures: sensors provide information about physical systems in the real world (physical layer), while computation modules (cyber layer) process the data to generate relevant information and decisions that may be fed back into the production process [3]. In this two-fold architecture the digital twin provides complete documentation about details of the manufactured part.

The paper is focused on the manufacturing process of carbon fibre composite parts, in particular on production processes that use lay-up of dry (i.e. not pre-impregnated) carbon fibers. Although the general concept of a digital twin covers the complete life-cycle of a part [5, 7], this work focuses on the carbon fiber lay-up process. Approaches for monitoring of such processes have been proposed in the past [8], [9]. For the experiments similar sensor systems are used to acquire raw data. Algorithms to process the large amounts of data produced by such sensors are proposed and it is shown how interesting high-level information about the manufactured part can be extracted.

Here the goal of generating a digital twin is to perform mechanical simulations to assess the effects that the variations of the production process and different kinds of defects have on the safety margins of the part. This requires the efficient description of a 3D part and all plies and layers (the so called ply-book) of carbon fiber material as defined in [10]. The modelling of composite materials and CFRP in particular is widely investigated, and there are different approaches that describe the material at the micro-, meso- and macro-scale.

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Recent developments are described in [11, 12, 13]. It should be noted that such finite element simulation is typically very time-consuming, while the use of a digital twin in this particular production environment typically requires response times of less than a few minutes. These questions, however, have just recently been addressed, e.g. in [4].

III. Production Process and Possible Defects

This section first describes the production process, the typical defects that are found in such processes and how they can be detected in real-time through suitable sensor technology. Furthermore it is explained which features are extracted from the raw data to generate the digital twin.

A. Carbon fiber lay-up processes and defects

Carbon fiber composite parts consist of multiple layers of carbon fiber material. Within each layer the material can either be uni-directional or some kind of woven fabric. In any case the orientation of the fibers is carefully selected when designing a part. The placing of the layers is either done by automated dry fiber placement (DFP), where multiple, small tapes of fibres are placed, or through automated dry material placement (ADMP), where much wider tapes of material are placed. After placing all the layers, the part is compacted and the infusion of the epoxy resin (Hexflow RTM 6) is done. This step is followed by a final curing process.

During the lay-up process a number of variations and defects may occur, that include e.g. gaps or overlaps in the material, distortions of the fabric, wrinkles or any kind of foreign objects. A few examples are shown in figure 1 below.

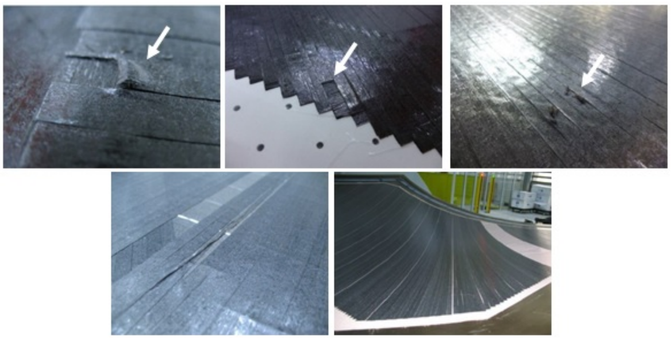

Figure 1: Various kinds of defects, such as wrinkles, early cut tapes, foreign objects (top row), and large gaps (bottom row).

Some of these defects can be the basis for delaminations in the finished part. For each of these defects different tolerances exist and re-work is currently required, whenever defects exceed these tolerances. Decision rules may be quite complex, considering also e.g. the accumulation of gaps within each layer or defects in the same or similar locations across several layers. The detection of the defects is very often done through human inspection after each layer. Recently, sensor systems have been developed that enable the automatic detection during the process.

B. Sensors for defect detection

The various kinds of defects can be detected by two different modalities: fiber orientation and 3D depth data. Whereas the first one enables the analysis of distortions in the material, the latter is used to determine gaps, overlaps and wrinkles.

For fiber orientation two different approaches exist. The first one performs texture analysis to determine the direction of the fibers, whereas the second technology uses a physical reflection model of carbon fiber to measure the orientation [9]. The raw data output of the sensor is a measurement of fiber orientation on a dense grid of pixels with a grid size of about 50x50µm. For typical part sizes as used in the aerospace industry, this would lead to excessive amounts of raw data. The defect analysis is thus done in line to avoid the accumulation of data. Defects are detected by assessing the difference between the expected direction of the fibers and the actual direction per pixel as measured by the sensor (figure 2). Deviations of less than ±3° to ±5° are often acceptable.

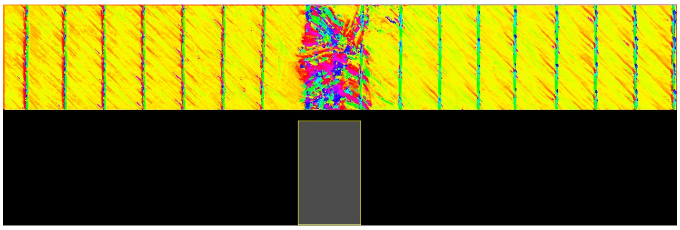

Figure 2: Detail in fibre orientations: color-coded fiber orientations (top) with defective region of unstructured material and the corresponding detection result indicated as a bounding box (bottom).

For determining the depth data a laser profile scanner is used. These sensors provide 2D profile data at high frequency of up to several kHz, depending on the surface properties and on the intensity of the laser. By continuously moving the sensor across the surface, a 3D surface model of the current layer is generated. The most important defects are gaps between neighboring tapes, that should not exceed certain tolerances (typically in the range of 0.4 to 1.5mm) but there are also criteria that relate to the accumulation of gaps within a certain region of the layer. Overlaps of neighboring tapes are not allowed as well as twisted tapes, where the tape is rotated by 180° along its longitudinal axis (figure 3).

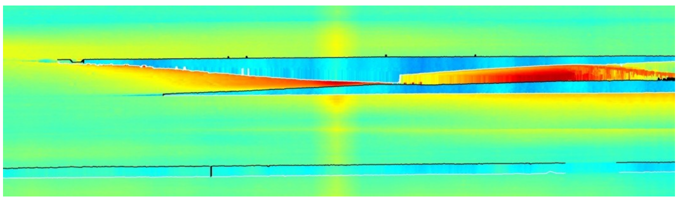

Figure 3: Depth image of a "twisted tow" defect and gap defect recorded by a laser profile scanner. Red color indicates elevated regions, blue indicates low regions.

Whereas in dry fiber placement 8-32 tapes are placed in parallel with a total width of up to 300mm, the ADMP process may place fabric with a width of up to 3000mm. In both cases the field of view of a single sensor is insufficient to cover the whole width at the required resolution. For this purpose a modular sensor design is used that allows the integration of several sensors so that – theoretically – any width can be covered (figure 4). Practically, the curvature of the part has to be considered, so that it is more useful to have a set of smaller modules that can be positioned independently.

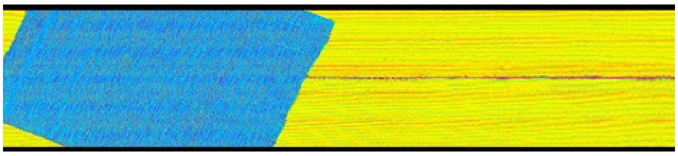

Figure 4: Fiber orientations from 5 sensors merged together to a single color-coded fiber orientation image. The blue area shows a patch of material with different fiber orientation and the dark line indicates a gap.

In terms of scanning processes there are different approaches. In some cases it is possible to perform the scanning during the placement process, provided that the requirements of the placement process and of the scanning process can be fulfilled at the same time. Alternatively, a separate, automatic scanning step can be used, which is slightly more time-consuming, but allows a flexible positioning of the sensors, thus leading to higher data quality.

C. *Features extracted for the digital twin*

After the pre-processing step that generates the fibre orientation data or the depth image, image segmentation is done. The segmentation is based on local histogram information, exploiting the fact that there are either one (in the case of unidirectional material) or two (in the case of fabric) main fiber directions. Pixels that significantly deviate from these main directions indicate a potential defect. By thresholding this deviation the contour of the defect is extracted. The contour is represented by a list of 3D coordinates along the boundary of the defect. From this contour the area and the bounding box of the defect are calculated. The area is required because it is a key feature to judge the severity of the defect and is thus a key criterion in quality control rules. The bounding box proved to be useful for further processing, e.g. when cropping the defect from the image and also when inserting it into the finite element model. The most important information that is determined from the segmented defect is its type. As mentioned in section III.B there are different types of defects such as winkles, fuzzballs, gaps, overlaps, foreign objects, … and for each of these defects different quality rules apply and they also need to be treated differently when assessing their impact on the mechanical properties. The defect type is determined through a classification method using histogram- and shape-based features that are used as input to a random forest classifier [14].
The defect position on the part is calculated based on an intrinsic and an extrinsic (hand-eye) calibration of the sensor relative to the machine. By back-projecting the defect from the image onto the 3D part, its position can be accurately determined and it can be inserted in the correct location for the mechanical calculation.
These data (position, area, bounding box, type) are sufficient to perform the mechanical calculations. The next section provides information on how to organize the "manufacturing database" to enable an efficient, inline "effects of defects"-calculation.

IV. System Architecture

To obtain a digital twin of the manufactured part, the sensor data need to be collected in a structured format that can be used as a basis for the calculation of the mechanical properties. The manufacturing database is intended to collect data from sensors and forward these data to simulation tools that will in turn enhance the data with simulation results. These are then fed back to the process, where decisions about re-work and process adjustments are made.

A. *Overall Architecture*

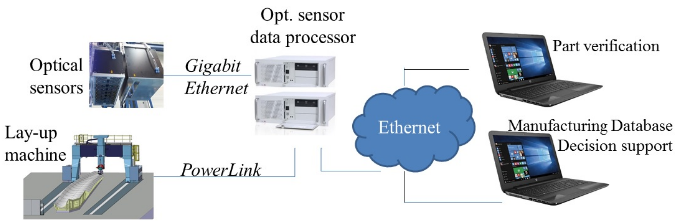

Figure 5: System layout.

The system layout is shown in figure 5. Data from the sensors are collected through Gigabit Ethernet, while machine (position) data are acquired through PowerLink connection. All of these data are merged in two industrial PCs that do the low-level processing. Defect data are transferred to two independent PCs, of which one performs the part verification and the other one is used to host the manufacturing database. In terms of data transfer the largest amount of data is transferred via the Gigabit Ethernet link from the sensors to the industrial PC. The network is used up to its limits, but this does not create a real bottleneck, because the sensors are working at maximum speed (frame rate). Data traffic in all other parts of the network is smaller by several orders of magnitude and does not create any impact on processing or production speeds.

B. *Structure of the Manufacturing Database*

The database uses the HDF5 file format [15], which provides a flexible structure to enable the storage of multiple different data. The HDF5 standard is widely used in domains such as geo-spatial data acquisition, bio-informatics, and other fields where large amounts of (binary) data need to be stored. The design was chosen such that an extension of the proposed file structure is easily possible. Within the HDF5 standard a tree structure is defined for our digital twin and all the numerical data are stored at the leaves of the tree, see figure 6.

Each *feature* (defect) can have a measured value (*manufactured* in the database structure) and a simulated value (*simulated*). These numerical results are classified into three types:

(1) Those which are measured across a region of the manufactured component and typically will be simulated for the whole ply, such as fiber direction. Such data will always be recorded in the database and they are usually related to a set of connected result points in the mesh of the part.

(2) Those which are measured at any point on the components, typically at a discrete set of user-defined locations. Such data include e.g. temperature or resin cure measurements. These measurements are linked to specific locations in 3D space (represented by x, y, z coordinates in the part coordinate system).

(3) Those which might happen at a specific location, such as any kind of defect that occurs during manufacturing. They will be recorded in the HDF5 file whenever certain thresholds are exceeded. This filtering according to the threshold already takes places in the sensor software.

```
composite_manufacturing
  features
    manufactured                Attributes: tolerances for measurement
      ply_based
        plyName                 (Container: list of manufacturing_features for a given ply)
          feature.N             m (Container: result set), attributes:
                                type [Overlap|Gap|Splice|Curvature|Unknown[4]], length, width, area[5], alignment [6]
            bounding_box        m (Data: double[2,3]), in global coordinates[7]
            boundary            m (Data: double[r,3], boundary points of defect polygon), attributes:
            preview             m (Data: double[num_rows,num_cols,3], grid of points for 3d surface of polygon
      component_based           (Container: list of manufacturing_features not associated with a specific ply)
        feature.N               m (Container: result set), attributes:
                                type [Overlap|Gap|Splice|Curvature|Unknown], length, width, area
          bounding_box          m (Data: double[2,3]), in global coordinates
          boundary              m (Data: double[r,3], boundary points of defect polygon), attributes:
          preview               m (Data: double[num_rows,num_cols,3], grid of points for 3d surface of polygon
    simulated                   Attributes: tolerances for definition
      ply_based
        plyName                 (Container: list of manufacturing_features for a given ply)
          feature.N             m (Container: result set), attributes:
                                type [Overlap|Gap|Splice|Curvature|Unknown], length, width, area
            bounding_box        m (Data: double[2,3]), in global coordinates
            boundary            m (Data: double[r,3], boundary points of defect polygon), attributes:
            preview             m (Data: double[num_rows,num_cols,3], grid of points for 3d surface of polygon
      component_based           (Container: list of manufacturing_features not associated with a specific ply)
        feature.N               m (Container: result set), attributes:
                                type [Overlap|Gap|Splice|Curvature|Unknown], length, width, area
          bounding_box          m (Data: double[2,3]), in global coordinates
          boundary              m (Data: double[r,3], boundary points of defect polygon), attributes:
          preview               m (Data: double[num_rows,num_cols,3], grid of points for 3d surface of polygon
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Figure 6: Tree structure of the manufacturing database.

Structurally there are two main elements. The first one includes the design data, such as the single plies, material data and 3D meshes and is used for simulation of the part as designed. The second, the actual manufacturing database, provides a tree-like structure to collect all data acquired during the manufacturing process. In the first hierarchy level there are the actual positions of datum points and plies. With respect to collecting defect information, the following nodes in the tree are relevant:

Events - Data are collected about e.g. when each ply was finished, when simulation results became available or when the curing process was started or finished. These data serve the purpose of documentation and – more important – help the synchronization of the various programs that access the database.

Field Result Sets - This includes data that are measured across a region (i.e. type (1)) as mentioned in the previous paragraph. Each entry contains simulated and measured values.

Features - *Features* include all the defects that are found by the sensors. Two different subcategories are distinguished: defects that are located within a single ply ("ply-based") and defects that pass through several layers ("component-based"). Per *Feature* the previously mentioned defect data (boundary, area, bounding box, type) coming from the sensor system are stored. Additionally, each feature is enhanced with a "margin of safety" consisting of the initial margin of safety, the one resulting from a quick, analytical calculation and (optionally) one coming from a detailed, finite element analysis. These safety margins are the main input to any decision making about the defect.

C. *Growing the digital twin*

As described in section III the sensor systems are processing the data during the manufacturing. This is organized through a pipeline, so that results are available more or less immediately after the ply is finished. Processing is (almost) equally distributed among two industrial PCs. The pipeline consists of five parallel threads, each dealing with one camera by merging image and position data. This is followed by fibre angle calculation (5 threads in parallel) and extraction of defects (again 5 threads). A single thread then takes up the defects and writes them into the manufacturing database. Data about the defects are written into the *Features* node of the HDF5 file. This is done asynchronously, whenever defect data become available. As soon as all defects for a single ply are processed, which will typically happen a few seconds after the ply has been laid, a new entry is made in the *Event* node of the database, stating that the defect processing is done.

The simulation software is continuously polling these events and as soon as it receives the information that the defect data are complete, it will start the processing. The initial processing will be done through the analytical model to quickly obtain a first estimate about the margin of safety. In the current implementation a detailed, finite-element calculation is done only based upon a user request, which will typically happen for critical defects that require deeper analysis. In any case the simulation results are added to the database and the margin of safety is added to the *Features* node.

Finally, there is the decision support tool that checks the events every 15 seconds and displays updated information about the manufacturing process and the simulation results to the user. At the end of each ply these results are used to decide about re-work options.

The whole process is repeated for each ply, i.e. simulation, decision making, and re-work take place after each ply.

D. *Predicting mechanical properties*

The purpose of the manufacturing database is to provide the necessary input data for assessing the mechanical properties of the part under a given load scenario. Finite element methods are the standard approach to perform such calculations. However, given the complexity of the part it is obvious that such calculation cannot be done within the time limits that are needed to make decisions in a manufacturing process. Instead, an approach is used where the whole part (as designed) is pre-calculated and the defects are inserted into this model. For each defect the reduction of the safety margin ("knock-down factor") can be calculated quickly and a decision can be made about how the defect needs to be treated. This concept is based on recent developments in [4] and shown in figure 7 below.

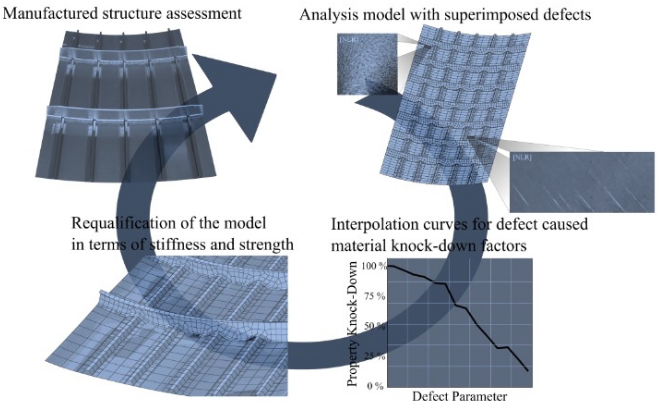

Figure 7: Analysis method to efficiently determine the effects of defects in a composite part [1].

The assessment of each defect can follow a two-step approach. An analytical model, that provides a result within a few seconds, is used to quickly give initial information whether the defect will be critical. For defects that require a more detailed analysis, a finite element solver is used. This takes a few minutes, but is still by many orders of magnitude faster than the re-calculation of the whole part including the defect.

The analytical model reads the defect data for the ply from the manufacturing database and determines the location of the defect. It will interrogate the results file for the strain at that location. Using the loading information, the manufacturing process specifications and the ply stacking, several calculations are performed according to the specificities of defects:

- The defect locally modifies the stiffness of the ply which contains this defect. Therefore, stresses in the laminate are redistributed according to their specific stiffness and the type of defect,
- the defect generates a various range of deviations (void, variation of fibers volume fraction, misalignment of fibers, …). Due to those defects, neighboring plies are waved, which drastically decreases their strength properties.

To ensure that the effect of defects is properly taken into account, the analytical models will estimate the strength reduction due to the waviness or the ply variation according to the manufacturing process. Mainly compressive and transverse strength are reduced. In fact, tension strength is highly sensitive to the stiffness and strength of the fibers. The most challenging task is to be able to consider in the analytical model both the ply with defect and the multi-layer properties of the composites.

The algorithm calculates a margin-of-safety for the undamaged layup and for the layup with the defect included. This data is written back to the manufacturing database for use by the decision support tool.

For the defect analysis a local approach is chosen, because a calculation of the full part at the required level of resolution is infeasible in a real-time environment. The detailed defect calculation is thus implemented as a local finite element sub-model of the global analysis. The defect boundary is used to define a local, orientated bounding box and this is used to cut out a section of the model, including a region of unaffected material. This area is meshed with a detailed 2D mesh and the ply stacking is retrieved for all elements. Any elements within the defect are assigned to a defect group. This information is passed to a routine that inflates the 2D mesh to a full 3D mesh. - each element in the 2D mesh will have a solid element for each ply present. This is done twice – first using the original stacking alone, and secondly using the stacking with an adjustment to account for the defect – e.g. for a gap defect the ply thickness within the defect is set to zero; for an overlap the thickness is doubled.

Both models then have boundary conditions applied from the original 2D global analysis – the displacements for the edge nodes are retrieved from the original FE result file. Once the static analysis has been run, a failure criterion is applied to get margins of safety for all elements. The worst case margin-of-safety for the first and second model is used to determine a reduction in the properties due to the defect. Again the margin of safety information is stored in the manufacturing database so that the decision support tool can use it.

V. Results

For the experiments a modular version of the Profactor FScan (fiber orientation measurement) and LScan (depth data) sensor were used to cover the whole width of the material in an ADMP process, where unidirectional non-crimp-fabric was placed on a slightly curved part. The design of this test part was based on a section of an A350 wing lower cover, as shown in figure 8.

Figure 8: Setup for ADMP part manufacturing. Carbon fiber material is automatically placed and inspected.

To complete one part 16 layers were placed where 9 layers covered the complete area of the part and the remaining layers are so-called "pad-up" layers that make up a thicker region of the part. Lay-up and scanning of a single layer took between 4 and 10 minutes in the experimental setup, depending on the amount of material to be placed. Scanning of a full layer with the FScan takes roughly 1 minute, for the LScan 45 seconds. Raw data delivered by the sensor hardware is approximately

10GB for the FScan and just 15MB for the LScan per layer. This large difference in the amount of raw data stems from the fact that the LScan sensor performs laser line extraction directly on the integrated camera and only provides individual laser line profiles (3D point cloud) as raw data. The FScan on the other hand requires 8 overlapping images with different illuminations to be taken at all locations over the surface.

Figure 9 shows contours of regions for which the local distribution of fiber orientations deviates from the regular pattern of the carbon fiber fabric. The input data are the ones shown in figure 4, where a misaligned patch (blue in figure 4) is placed across the material (yellow in figure 4) and a gap between two pieces of fabric is visible (black in figure 4). Edges of the fabric with deviating fiber orientations and a gap between neighboring fabrics are extracted as contours. The parallel white lines in figure 9 indicate the area covered by the sensor during this particular scanning pass. The contours are then back-projected onto the surface of the 3D model of the part. The same contours are stored in the manufacturing database. The analytical model for these defects needed just about 3 seconds to generate the knock-down factors for these defects. The detailed, finite-element model took about 5 minutes to complete the calculations. A quite good match between the analytical model and the detailed model is observed, but a more in-depth investigation is still needed.

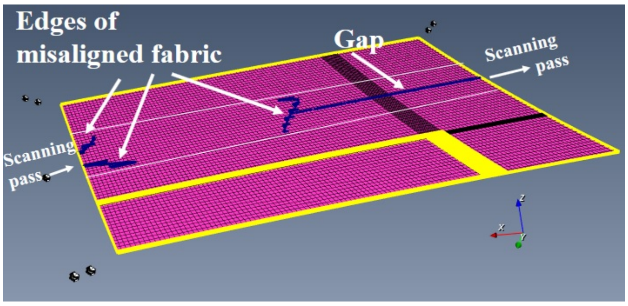

Figure 9: Features representing ply boundaries and gap back-projected onto the surface of manufactured part.

The main conclusions from the experiments are that it is possible to collect all relevant information needed for setting up a digital twin of a composite part in real-time and during the production process. The impact of the defects can be calculated in (almost) real-time using an analytical model and only in the case of critical defects a finite-element model is needed that takes about 5 minutes to generate a results. This performance is sufficient to be used in real-world production scenarios and does not have negative impact on productivity. The match between the analytical model and the finite-element model still needs to be evaluated in detail.

Future work will focus on the decision making process. The decision whether or not re-work is needed for a defect depends not only on its severity in terms of reduction of safety margin, but also on how quickly it can be corrected, how many non-critical defects were already left in the part and how many are to be expected before the part is finished. This will require predictive models to be included in the decision making.

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VII. References

[1] Falk Heinecke und Tobias Wille: From as-designed to as-built analysis using an multiscale approach and model update. EASN – 5th Int. Workshop on Aerostructures, 2 – 4 September 2015, Manchester, United-Kingdom

[2] Fei Tao, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, Fangyuan Sui: Digital twin-driven product design, manufacturing and service with big data. International Journal , 2017, https://doi.org/10.1007/s00170-017-0233-1

[3] Kazi Masudul Alam and Abdulmotaleb El-Saddik: C2PS: A Digital Twin Architecture Reference Model for the Cloud-Based Cyber-Physical Systems. IEEE Access, volume 5, pages 2050--2062, 2017, https://doi.org/10.1109/ACCESS.2017.2657006

[4] Michael LeGault, Nondestructive inspection: Better, faster and cheaper, in High-Performance Composite, Nov. 2013

[5] Eric J. Tuegel, Anthony R. Ingraffea, Thomas G. Eason, and S. Michael Spottswood: Reengineering Aircraft Structural Life Prediction Using a Digital Twin. International Journal of Aerospace Engineering, Volume 2011, Article ID 154798, http://dx.doi.org/10.1155/2011/154798

[6] Li Da Xu, Wu He, Shancang Li: Internet of Things in Industries: A Survey. IEEE Trans. Industrial Informatics, volume 10, number 4, pages 2233 -- 2243, 2014, https://doi.org/10.1109/TII.2014.2300753

[7] Edward Glaessgen and David Stargel: The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Structures, Structural Dynamics, and Materials and Co-located Conferences, April 2012, https://doi.org/10.2514/6.2012-1818

[8] S. Zambal, W. Palfinger, M. Stöger, C. Eitzinger: Accurate fibre orientation measurement for carbon fibre surfaces. Pattern Recognition Journal, Volume 48, Issue 11, November 2015, Pages 3324–3332, doi:10.1016/j.patcog.2014.11.009

[9] S. Zambal, W. Palfinger, C. Eitzinger: Robotic inspection of 3D CFRP surfaces. 3rd IEEE International Workshop on Metrology for AeroSpace, Florence (Italy), June 22-23, 2016

[10] Klintworth and McMillan (1992), "Effective analysis of laminated composite structures", Benchmark, NAFEMS, December 1992

[11] B. Bielefeldt, J. Hochhalter, D. Hartl (2015) Computationally efficient analysis of SMA sensory particles embedded in complex aerostructures using a substructure approach. ASME 2015 Conference on Smart Materials, Adaptive Structures and Intelligent Systems, 2015

[12] Falk Heinecke, Wouter van den Brink, and Tobias Wille: Assessing the structural response of automated fibre placement composite structures with gaps and overlaps by means of numerical approaches. 20th International Conference on Composite Materials, 2015

[13] Zhong Hu, Ranjan Karki, Prediction of mechanical properties of three-dimensional fabric composites reinforced by transversely isotropic carbon fibers, Journal of Composite Materials, Vol 49, Issue 12, 2015

[14] Breiman L., Random forests. In Machine Learning, Seiten 5–32, 2001

[15] https://portal.hdfgroup.org/display/HDF5/HDF5