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A cloud-based digital twin for monitoring of an adaptive clamping mechanism used for high performance composite machining

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Abstract

In this work, we present a cloud-based digital twin for monitoring of a clamping technology for machining of composite parts. Supporting large and/or freeform composite parts is crucial to avoid bending during drilling. Bending of the part will lead to delamination and frayed edges of the drilled holes. The new active clamping technology allows to realize a stabilized fixture, localized in the area where the drilling occurs, to avoid bending. This significantly improves quality of the drilled holes. The clamping device is equipped with an IoT edge device, with a bidirectional communication to the cloud. The cloud-based digital twin analyses the quality of the drilled holes based on computer vision, monitors the drill wear and detects incorrect operation of the active clamping device. All data is stored in the cloud to gain new insights in the operation of the drill with active clamping device. The full deployment occurs on the Microsoft Azure cloud platform. This transforms the standard machine into an Industry 4.0 compliant machine.

Keywords: Digital twin; cloud; smart manufacturing; tool monitoring; quality control

1. Introduction

Today's industry is in need to make manufacturing processes more digital and realize a more intelligent operation. Standard machines need to become self-aware and self-learning machines, that increase their overall performance and maintenance management, leveraging the value of different data sources [1]. Real time data monitoring, tracking the

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status and positions of a product as well as to hold the instructions to control production processes are the main needs of Industry 4.0 [2]. A key concept in realizing these intelligent machines is the digital twin. In most definitions, a digital twin is considered as a virtual representation that interacts with the physical object throughout its lifecycle and provide intelligence for evaluation, optimization, prediction, etc [3]. [4] proposed that a complete DT should include five equally important dimensions: the physical part, the virtual part, connection, data, and service. The authors of [5] propose a classification of Digital Twins into three subcategories, according to their level of data integration: 1) A digital model, 2) A digital shadow, 3) A digital twin. According to this definition, the data flows between an existing physical object and a digital object are fully integrated and automatic in both directions for a digital twin, this in contrast to a digital model or digital shadow. According to this definition, the digital object might also act as controlling instance of the physical object. The introduction of digital twins in industry will allow companies to realize value and benefits faster than ever before.

Machining of flexible composite plates

Within this work, we demonstrate the use of a digital twin for the monitoring of a machining operation of composite materials. Composites are frequently being used in several applications, like aerospace or automotive. Machining flexible composite plates remains challenging. First of all, the cutting forces caused by the anisotropic properties, high stiffness, and high abrasiveness of fibers in composite materials are leading to high cutting tool wear [6]. Next to that, when insufficiently supported, these plates will bend during drilling, resulting into quality issues like delamination or fiber break-out. Different clamping solutions exist in the state-of-the-art, but these are too expensive and/or provide insufficient flexibility for the machining of low-volume, high-variability pieces [7]. Therefore, a new patented clamping technology was recently proposed that allows a stabilized fixture, localized in the area where the cutting operation occurs [6]. This clamping system can be applied in combination with low-cost supports, and can be adapted to deal with freeform shapes. It can be installed as an add-on to a CNC machine center and can be a flexible and low cost solution for machining of low-volume, high-variability pieces.

Literature review: Digital twins for monitoring of a machine tool

A general overview of digital twin applications in industry is given in [8] and a review for applications in manufacturing is given in [9]. For the specific application of monitoring a machine tool, several authors have presented a digital twin. These however do not leverage all benefits of a cloud-based digital twin, since data storage, visualization and/or monitoring algorithm deployment often occurs at a local PC or is missing. Also the data flows between the physical object and the digital object are often not fully integrated in both directions. In [10] a digital-twin of a 3-axis vertical milling machine is presented to monitor surface roughness, running on a local PC. [11] addresses the challenges of data communication and management with a CNC machine tool using the MTconnect protocol, whereas the authors of [12] address the problems of data management and analytics for a digital shadow in the machining industry. [13] presents a digital shadow for tool wear monitoring, with a physical model based approach. In [14] a digital twin of a cutting tool is described, where the digital twin of the tool is communicated according to an information model, over a newly developed flexible information architecture. [15] presents a multi-domain modelling method used for fault prediction of a ball screw within a CNC machine. In [16] a digital twin model that is suited for machine tool design and optimization is presented, whereas [17] presents a digital twin driven-data flow framework for cutting tools. There is a tremendous benefit of the Digital Twin for applications in industry, but there is still a lack of case-studies which apply the concepts in practice [5], especially for maintenance and monitoring applications.

Paper contributions and outline

In this work, we connect an Internet-of-Things (IoT) edge device to an innovative clamping device, and we demonstrate how to combine machine data and real-time data from different types of sensors with advanced analytics in a cloud-based digital twin for monitoring of this clamping technology for machining of composite parts. Three different new monitoring algorithms are part of the developed digital twin: 1) Quality monitoring of the drilled holes, 2) Indirect tool wear monitoring, 3) Indirect clamping monitoring. These monitoring algorithms help to reduce the amount of scrap material, by immediately informing the operator to fix or replace parts, or by automatically stopping the machine. Next to that, automatic monitoring by the digital twin can help to replace other time consuming quality monitoring steps, like visual inspection by operators. Finally, data from the production process is also stored in easy

queryable databases, which can in a next phase be used for off-line process optimization based on data analytics, e.g. correlating product quality with production parameters. Data is stored and easily accessible in the Azure cloud, and all algorithms run as serverless compute functions on the cloud. It is shown how a digital twin for machine tool monitoring can be made by means of a commercial cloud computing platform like Microsoft Azure, and the selection of the different components of the cloud architecture are being discussed. The paper is structured as follows. In Section 2 the innovative clamping device is presented. All sensors as well as the edge device will be discussed. Section 3 describes the different monitoring algorithms which are part of the digital twin. In Section 4 the cloud architecture is explained. Conclusions are made in section 5.

2. Machine setup

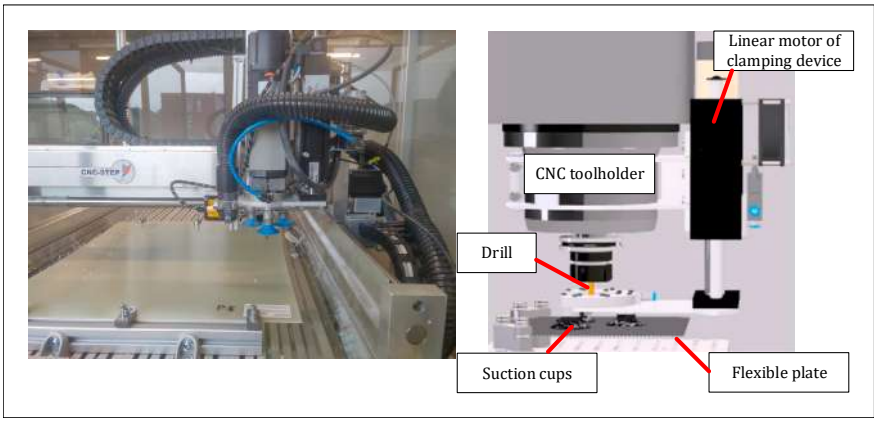

Fig. 1. CNC machine with add-on clamping device used within this work (left) and zoomed picture of the different components of the add-on clamping device (right)

A picture of the research setup used in this work is presented in Fig. 1, which is a CNC machine for drilling holes in flexible composite plates. The clamping system is attached to the CNC toolholder and moves along with the drilling head. When drilling takes place, it will provide support locally around the drilling location by clamping the plate from the top. Suction cups powered by a vacuum generator realize this clamping. Connecting or releasing can be done using electronically driven valves. While the drill moves towards the plate, the suction cups move in the opposite direction, compensating for the motion of the drill to the plate. This motion is realized by an independent linear motor. The controller of the clamping system allows to compensate for the drilling forces to keep the workpiece steady. More information on the clamping operation can be found in [6] or in a video [18]. This clamping device is added as an add-on to a CNC machine for drilling composite plates. This machine is equipped with several sensors, that allow to log:

- Current of the linear motor of the clamping device, providing a clamping force estimate.
- Z-position of the linear motor of the clamping device
- Deflection of the plate
- X-Y-Z position of the CNC machine
- CNC machine state

The data is available on the CAN-bus and logged by a PC with an external CAN connector. Data is sampled at 500Hz and averaged per 5 samples. This PC serves as the IoT edge device, which is used to connect the device to the cloud via Azure IoT Hub [19]. For every drilled hole, data is collected together in one batch. This batch is then sent from the edge device to the cloud. After a hole has been drilled a camera image of the drilled hole is automatically taken, which is also sent to the cloud. The experiments presented in this work are all obtained with

glass-fibre composite plates with dimensions of 620x540mm and a thickness of 2mm and drilled with solid carbide drills with a diameter of 6mm.

3. Monitoring algorithms

3.1. Hole quality monitoring

A camera takes a picture from every drilled hole. A computer vision algorithm then measures the quality of the hole by quantifying the amount of delamination of the composite caused by the drilling.

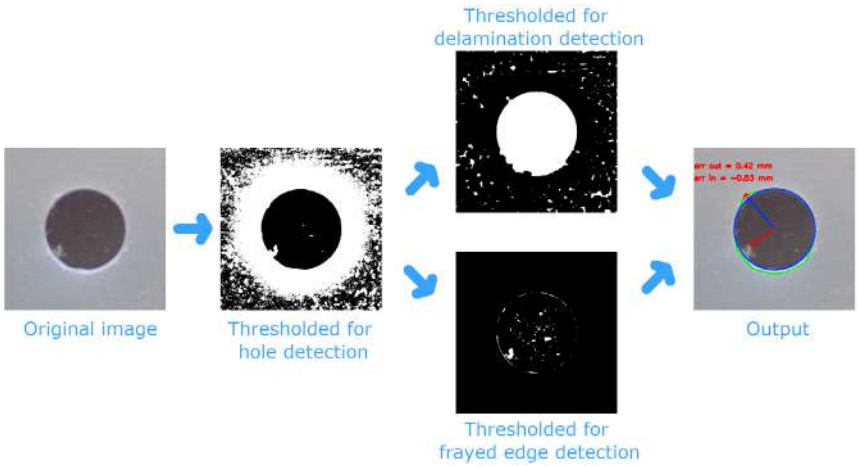

Fig. 2. Input, intermediate images and output of the computer vision algorithm to measure delamination and frayed edges, applied on an image of a hole.)

The algorithm starts by converting the image to grayscale and applying an adaptive thresholding algorithm. Since the hole should approximately be in the center of the image and the contrast between hole and black background is large enough, detecting the hole (and its center and radius) is then fairly straightforward. In a next step, we again apply adaptive thresholding (with different settings) to segment the white borders around the hole that are a result of delamination. We look for delamination regions close to the hole; the farthest point of these regions to the hole center is measured and used as a measure for the degree of delamination caused by the drilling. The algorithm similarly inspects frayed edges on the inside: we apply adaptive thresholding to identify the closest point of composite material to the center of the hole (that is still directly connected to the hole's edge). An example of an original picture, the intermediate thresholded images and the processed output can be found in Figure 2.

3.2. Indirect tool wear monitoring

A worn drill will directly affect the end quality of the workpiece. Next to that, it will result in an increase of the energy consumption to drill the hole by the CNC and of the clamping device, which will need to compensate for higher feed forces. Several methods for tool condition monitoring in drilling exist, which can be classified into two categories: direct and indirect methods [20]. Direct methods try to measure tool wear directly, by a form of visual inspection of the tool edges. Indirect methods use another sensor signal, to estimate the tool wear. These include monitoring methods based on drill torque, feed force, vibrations, sound, etc.. It is generally known that cutting forces increase as tool wear increases [21]. Monitoring forces in a cutting process in order to follow the development of cutting tool wear is therefore a logical choice. In this work, we have implemented an indirect tool wear measurement. The position control of the add-on clamping device tries to compensate for feed forces that bend flexible plates, and the clamping force, derived from the measured current, is therefore an indirect measurement of the feed force. While it might not always be easy to add a feed force measurement to the CNC machine, the clamping device provides an estimate of it.

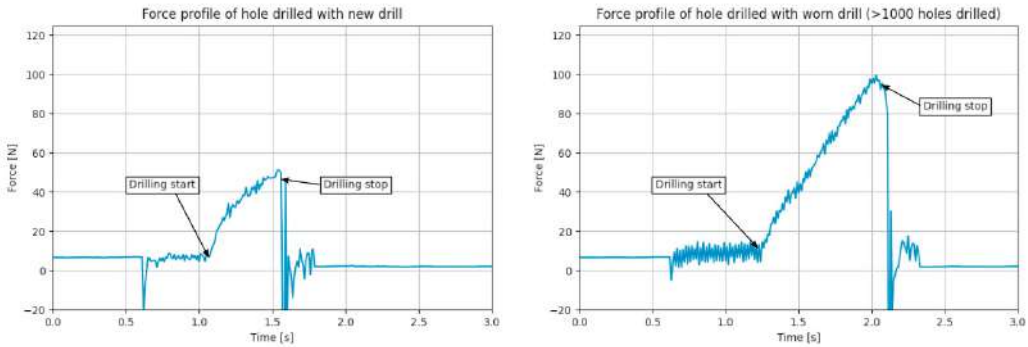

Fig. 3. Clamping force for a new drill (left) and worn drill (right)

Fig 3 shows the clamping force profile during drilling. It presents the profile for a brand new drill (left) and the profile for a worn drill, which already drilled more than 1000 holes (right). It is indicated where the drilling starts, resulting in a force build up, and where the drilling stops, resulting in a drop of the force. An increase of the force is visible when the drill has undergone tool wear. Different statistical parameters of the feed/clamping force can be used to keep track of the tool wear. Within this work, we use the clamping force to calculate an estimate of the energy required to move the drill down during the drilling operation (starting at t_1, ending at t_2). Having an estimate of the feed force (F_t force in function of time t) and measurement of the drill movement ($v = \frac{dz}{dt}$), the energy estimate can be computed as follows:

$$W = \int_{t_1}^{t_2} v F_t(t)\, dt \tag{1}$$

Fig 4 presents the energy estimation for a series of holes that are drilled (left). The figure clearly shows an increase in the estimated energy measure as more holes are being drilled, caused by slowly occurring drill wear. Due to the variance on the results related to the setup, the estimate is further improved upon by calculating a moving average over the last five drilled holes, as shown in Fig 4 (right). For each newly drilled hole, this measure can now be used to calculate the relative increase with respect to an initial value that represents a brand new drill. A maximum allowable increase of energy with respect to this initial value of a brand new drill is identified, which will be used to define if a drill is fully worn out. This maximum value can be experimentally identified by drilling a test piece with a worn drill, which can be selected by an experienced operator. Alternatively a ground truth profile measurement of a drill, created using a high-end 3D optical microscope can be used to check the level of wear, to select a worn drill. For each drilling action, the margin to this maximum value can be computed, providing an estimate of the drill wear. The initial and maximum allowable energy value have to be made adaptive to different parameters of the machining process, such as drill diameter or plate material.

3.3. Clamping monitoring

Different types of failure can occur with the clamping system itself, resulting in a poor or even no support of the flexible plates. This could for example be due to damaged suction cups, or a loss of vacuum. As there is a direct measurement of the force provided by the linear motor for clamping, it is pretty straightforward to detect proper operation of the clamping device during drilling: whenever drilling takes place, a minimal force is expected to be provided by the linear motor for clamping the flexible plate. Fig 5 presents the clamping force during normal operation (left) and an incorrect operation with a loss of vacuum (right). The algorithm therefore uses the maximum force during drilling, and compares this to a threshold. The threshold defining the classification boundary between correct and incorrect clamping operation can be made adaptive to the feed rate, drill diameter or plate material, to avoid any incorrect classification. An alternative detection of incorrect operation of the clamping device could be based on an additional deflection sensor measuring the plate deformation, but it is considered that this sensor would not always be available.

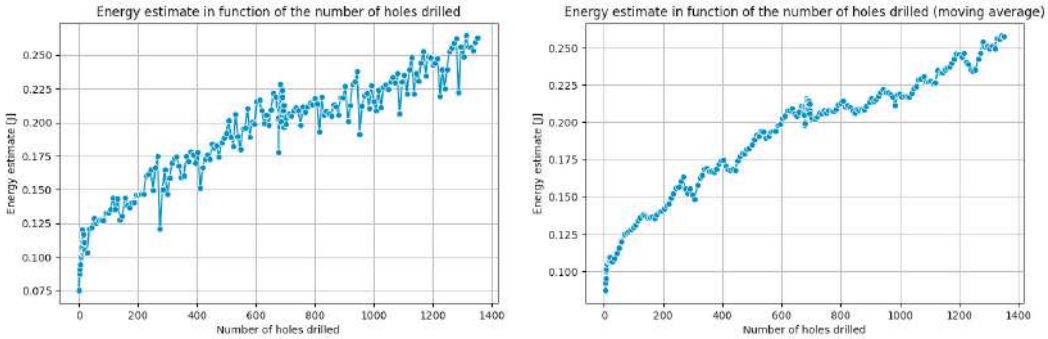

Fig. 4. Energy estimate in function of the number of holes that have been drilled: calculated estimate for each hole (left) and moving average over last 5 holes (right)

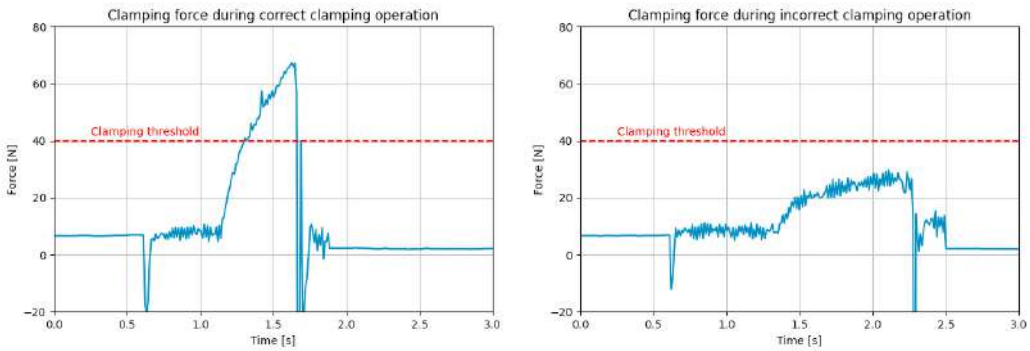

Fig. 5. Clamping force during drilling with correct operation of clamping device (left) and clamping force during drilling with incorrect operation of clamping device (right)

4. Cloud architecture

When deploying a digital twin there is freedom to choose which steps of the processing pipeline are being executed on the local Edge device and in the cloud. Exploiting the advantages of these different platforms, as well as, minimizing their disadvantages, is a challenging task due to the large design space and number of KPIs. Below the key pros and cons for the digital twin considered in this work are listed:

- Data Centralization: It is possible to store all data on the Edge device, however if you want to use data from different machines, you would need to send it between all the different edge devices. It is simpler to store everything in a central location (the cloud) instead. When storing data only locally, the risk of data loss increases. In the cloud, data can be stored (geo-)redundantly. It is also easier to query this data for new algorithm development or process optimization. E.g. off-line process optimization based on data analytics can be performed, to correlate product quality to production parameters, and optimize these parameters. Finally, a central data storage will make it easier to create a digital passport of the product and follow the product over its different production steps. For these reasons we have selected cloud data storage in our architecture depicted in Fig 6.
- Storage and performance limits: typical low-power, low-cost Edge devices are not built to store large amounts of data (memory) or invoke a high processing power for monitoring algorithms. This could be achieved by installing a costly high-end device next to each local machine, however it is more economical to do this in one centralized place instead (the cloud). Next to that, a central cloud deployment makes it easier to develop, add or change monitoring algorithms. Cloud data storage and cloud computation of the monitoring algorithm are therefore selected in our architecture.

- Bandwidth: Sending data between the edge and the cloud consumes bandwidth. For this reason, it is chosen to perform the batching and calculations on sample level on the edge: it avoids sending every sample individually to the cloud and reduced the required bandwidth and its cost. Therefore our architecture includes pre-processing on the edge.
- Responsiveness: When performing the complete workflow on the edge, no (back and forth) communication with the cloud is required. This would be faster, since the delays of transferring data are excluded. However, within this application, a delay of < 3 seconds for the monitoring of the quality of the drilled hole, the drill wear and the clamping device is considered acceptable, which is considerably less than the time between the drilling of two holes. Fulfilling this delay requirement is easily feasible with the architecture we selected.

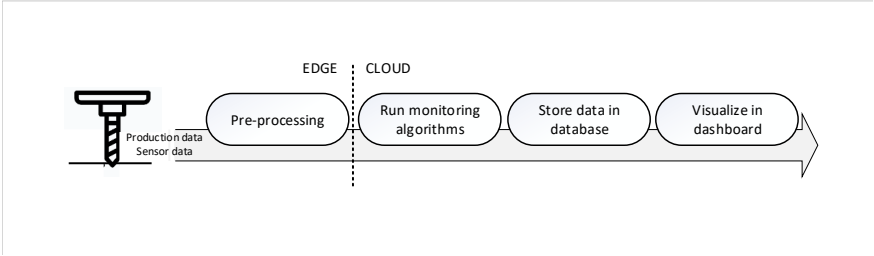

Fig. 6. Architecture of cloud-based digital twin

This architecture is further detailed into the deployment on Microsoft Azure depicted in Fig 7.

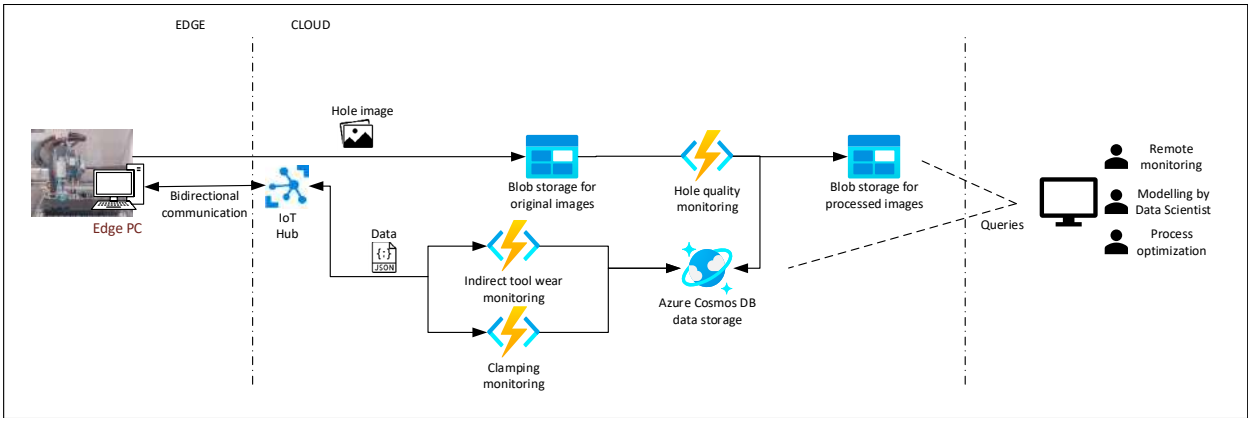

Fig. 7. Deployment of cloud-based digital twin

The edge computer sends the hole image and hole data each time a hole is drilled to the cloud via Azure IoT Hub. Azure IoT Hub is a managed service, hosted in the cloud, that acts as a central message hub for bi-directional communication [19]. Each time a workpiece or drill gets changed, the operator puts in the necessary information of the workpiece/drill and the corresponding data is send to the cloud. Arrival of a new image or hole data package triggers an event, which will trigger the different monitoring algorithms. The three different monitoring algorithms are implemented as Azure Functions. Azure functions are serverless compute solutions that can run code as certain events occur [22]. In this application, these events are the arrival of a new hole image (for the hole quality monitoring) or the arrival of a new batch of hole data (for the monitoring of the drill wear and clamping). With the help of Azure IoT Hub bidirectional communication and Azure functions, the machine parameters can be automatically modified when the monitoring algorithms detect abnormal behavior. Subsequently, all data gets stored in the cloud. The machine data, plate data, drill data and all hole related data (production and sensor data) are stored in a CosmosDB document database in separate collections. A CosmosDB document database is a fast NoSQL database, which is more flexible than conventional relational databases. In this type of database, it is easy to integrate new information. For example it

is easy to extend the document of a single hole with the data of an additional post processing or monitoring step, like a CMM (Coordinate-Measuring Machine) measurement of the drilled hole, or when a new sensor would be added to the setup. Intuitive query languages are available to access the data, which can be used by a data scientist to further improve the monitoring algorithms presented before, or to analyze the data to improve the process parameters. We apply a normalized data model, as there are several one-to-many relationships: A single drill will create many holes, each device will create many holes, and a plate can have multiple holes. Fig 8 represents the data structure. A typical document of a single hole has approximately 200kB of data, due to the presence of sensor data during drilling, whereas a document of the plate, drill or device are below 1 kB.

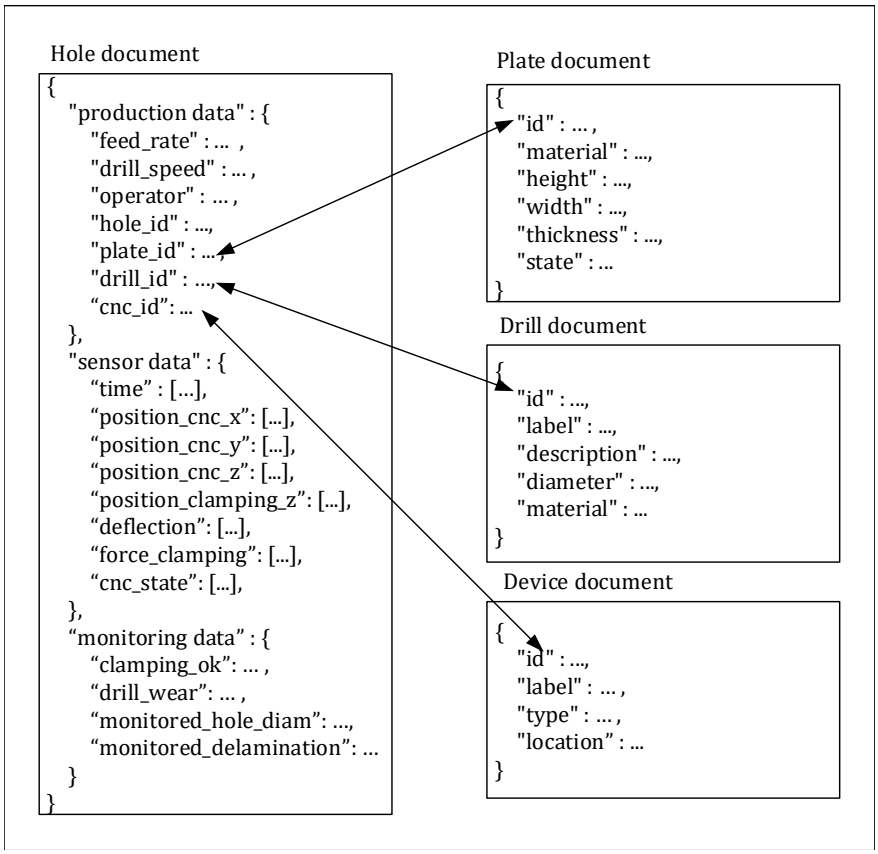

Fig. 8. Data structure of data stored in a document database

The images of the drilled holes are stored in an Azure Blob storage. Azure Blob storage is a service that stores unstructured data in the cloud and is well suited for storing media files. Both the original as the processed images are stored. Within the document of each hole, a link to the images is stored. A web application is developed to visualize the information of the digital twin to the operator. This web application is developed using HTML, CSS, Javascript and Flask. Fig 9 shows the dashboard of the digital twin of a drilled hole. It consists of the production data, the processed hole image and monitoring indicators that show the drill wear (with a gauge) and clamping operation during drilling (with a green/red light). Next to that, an interactive graph for the time-series sensor data is present. This dashboard is automatically updated. Similar dashboards are available for the digital twin of a drill or workpiece.

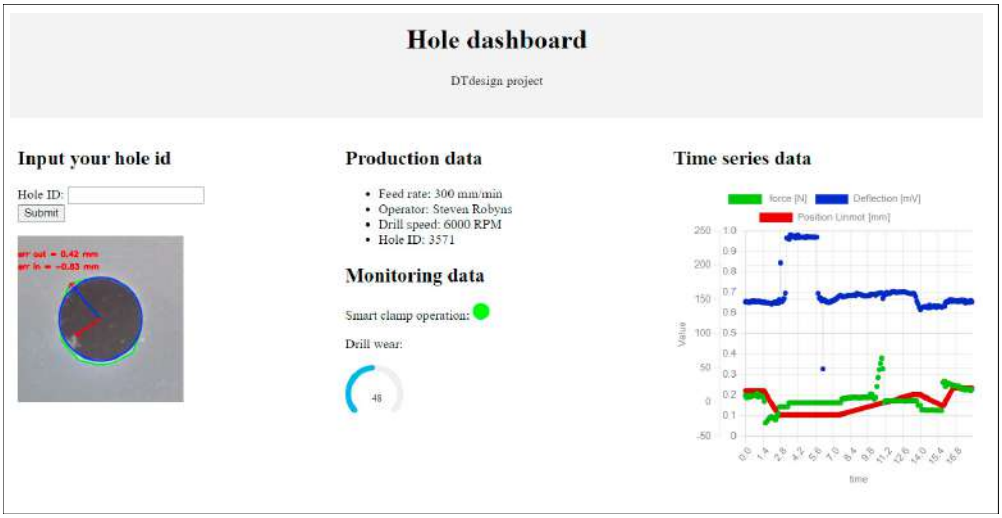

Fig. 9. Dashboard of the digital twin of a single drilled hole

5. Conclusion

Contributions

In this paper, an innovative clamping device for drilling flexible composite plates has been presented, for which a cloud-based digital twin has been developed. Three different new monitoring algorithms for this device have been implemented. First of all, an image processing algorithm provides information with respect to hole quality. Next to that, an indirect tool wear monitoring algorithm has been implemented, which use the clamping force for wear estimation. Finally, the clamping force is also used to asses correct functioning of the clamping operation during drilling. The innovative clamping device has been connected to the cloud via an IoT edge PC. When data is send to the cloud, it automatically triggers the monitoring algorithms. These algorithms can help to replace other time consuming quality monitoring steps (like a visual inspection by an operator) and will inform the operator immediately to fix or replace a part in case of an anomaly. This will shorten production time and reduce the amount of scrap material. It has been described how these algorithms are deployed in a commercial cloud platform, as part of a full cloud architecture. The selection for this type of edge-cloud architecture has been discussed, and could easily be applied to other machines as well. All data is stored in an easy accessible format, which enables off-line data analysis by data scientists, to for example optimize production parameters or further improve or add monitoring algorithms.

Limitations and Future work

In this work, data of a *single* production step is collected and used to make quality statements on the produced product. More advanced insights and quality statements can be made when data from the other production and assembly steps, but also from the product engineering phase, components and material suppliers, ..., are collected and integrated with each other. Since the data is collected from different sources and is of various nature (scalar data, time-series, 3D, relational, ...), the data will be stored in multiple, heterogeneous databases and files. A data scientist, or any other engineer, that wants to investigate the data will be confronted with this and will spend considerable time to search for the right data, thereby also trying to understand the context of the data, before it can actually be used. Therefore, we will work on the integration of a knowledge graph, which acquires and integrates information into an ontology and provides a central information access for data scientists [24]. While the knowledge graph captures the knowledge you have on the data, and thus give context to the data, the data of single asset should be better managed and accessible as well. The German industry 4.0 platform suggests to tackle this through a so called *Asset Administration Shell (AAS)* [25, 26]. OPC-UA is one of the protocols that can be used to implement such an AAS. Adding such an asset administration shell and integrating that with the knowledge graph approach is another part of future work that will be done. A last part of future work will go to updating the monitoring algorithms automatically with

the gathered data. Machine learning algorithms will be added to monitor the hole quality. The continuous addition of new data will allow to adapt/retrain these algorithms automatically in the digital twin of the device. Next to that, the data will be used to further optimize production parameters. This will result in a machine which is ready to be part of a smart factory.

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