Application potentials of Semantic Technologies for Digital Twins in Aircraft Design, Manufacturing and Maintenance

Milapji Singh Gill, Jonathan Reif, Tom Jeleniewski, Maximilian Weigand, Alexander Fay
Institute of Automation Technology, Helmut Schmidt University
Hamburg, Germany
{milapji.gill, jonathan.reif, tom.jeleniewski, maximilian.weigand, alexander.fay} @hsu-hh.de

***Abstract* – The digital twin (DT) is a lifecycle-spanning concept applied for the systematic management and efficient use of digital artefacts (data and models) associated to individual entities or entire system networks in the course of digitalisation. A multitude of data and models related to an aircraft with its components, processes and resources are collected during the design, manufacturing, operation and maintenance. The integration of such digital artefacts can, in turn, contribute to making workflows more effective and efficient in different lifecycle phases. However, such approaches usually fail due to the large number of different heterogeneous information silos and the difficulties in linking them with each other. In this context, semantic technologies (ST) have the potential to counteract such problems and to increase interoperability as well as reusability. The aim of this paper is to present the application potentials of ST for DTs of aircrafts with their components and systems in the life cycle phases design, manufacturing and maintenance. For this purpose, typical digital artefacts and the use of ontologies for the efficient management in DTs are described. In the first step, each life cycle phase is considered separately with its data and models for products, processes and resources, together with a description of the application potentials. In the second step, cross-life cycle application potentials are described.**

Keyword – Digital Twins, Data Management, Semantic Technologies, Aviation

I. Introduction

The increasing digitisation enables the integration and networking of different information sources with the aim to accelerate and improve inefficient, time-consuming processes [1]. In this context, the DT is gaining popularity in a wide range of domains [2–4]. The approach pursued for DTs is to map a digital representation of a product, a resource or even an entire process, including its behaviour, structure and functions, on the basis of a continuous data flow [5, 6]. The integrated data can then be used in combination with application-specific models to answer descriptive, diagnostic, predictive and prescriptive questions [3].

The use of DTs in the field of aviation offers potentials in a wide variety of use cases [7–9]. As described in Fig. 1, a large amount of data and models are generated and used in design, manufacturing, operation and maintenance throughout the life cycle of an aircraft and its individual components and systems [5-7]. However, the integration of these digital artefacts into the DT poses huge challenges. The prerequisite for the targeted use, networking and interoperability of DTs is the elimination of the prevailing information silos among the companies and life cycles involved. Isolated data must be combined in a semantically consistent manner to provide a uniform view of the systems, so that a simple access as well as a correct interpretation is enabled [1, 10]. Additionally, standardised interfaces are necessary to initiate an exchange of information between different partners in the value chain [3, 4, 11]. Proprietary approaches, such as those often found in the field of aviation, are contrary to this target. Ontologies from the field of symbolic artificial intelligence (AI) are a suitable means for formally describing the semantics of a domain as well as for linking existing information [1, 3, 10, 12]. In addition, they offer the possibility of generating considerable added value from data through the purposeful combination with other digital models (e.g. from the field of sub-symbolic AI or simulation models) [3, 4].

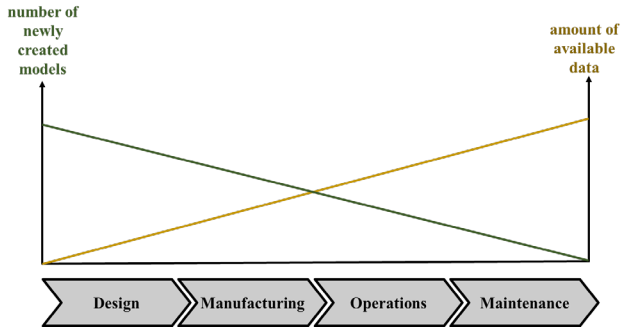

Fig. 1: Creation of models and data throughout the lifecycle of an aircraft, inspired by [3].

In the context of this contribution the application potentials of ST for DTs in different life cycle phases are analysed. For this purpose, Sec. II first introduces definitions and basic explanations of the DT and ST. Subsequently, related works on DTs in the field of aviation are discussed in Sec. III. Additionally, approaches of using ST in DTs as well as the benefits are outlined. Sec. VI. presents various application potentials of ST for DTs in the aviation domain. In this course, the individual phases of aircraft design, manufacturing and maintenance are examined in terms of data and models according to the product, process and resource principle. In this regard, different use cases are considered for the respective phases. In addition, the application potentials for the cross-lifecycle combination of data and models by using ST are presented. Sec. V summarises the contribution and provides an outlook on ongoing and future research activities.

II. BACKGROUND

Sec. II is intended to provide the background for this contribution. Therefore, definitions of the DT as well as a short description of ST are introduced.

A. Digital Twins

A number of definitions for the DT have accumulated over time, varying in some level of detail. A consensus among publications, in the endeavour to define the DT, is that a distinction should be made between a physical and a virtual space [5, 13]. In this case, the DT is part of the virtual space. The connection to and synchronisation with the counterpart in the physical space is created via a data flow [5]. DTs can be created from products, processes or resources that can interact with each other through defined interfaces [4, 6]. Grieves et al. [13, 14] emphasise that the DT is suitable to manage models and data of a physical assets over the entire life cycle. A DT can in turn be used to answer various questions and improve processes, as mentioned in the introduction. There are different views on the designation of the various components or digital artefacts the DT should consist of. For example, Kritzinger et al. [5] distinguish between digital models, digital shadows and DTs, depending on the degree of integration realised by an automatic or manual data flow. The DT as the ultimate state of development is characterised by a bidirectional automatic data flow between physical and virtual space. A less rigorous definition of DTs is pursued by Stark et al. [15]: An automatic data flow back to the physical counterpart is not mandatory to be considered a DT. According to this definition, the digital shadow describes the data that is recorded during the life cycle. The digital master contains type models that are only instantiated when the physical counterpart is put into operation. Accordingly, the DT arises from the interaction of the digital shadow and the digital master. Other authors introduce further capabilities of the DT. Thus there are concepts of the 'intelligent' or the 'next generation' DT [4, 16]. Such publications include methods of AI or strive to enable interaction between different DTs.

In the context of this paper, the DT is seen as a concept characterised by the interaction of information in the digital shadow (time-dependent data) and various use case-specific digital models (see FIG. 2) in order to calculate and generate valuable new data. If an information model is added to the DT, an information flow (arrows in FIG. 2) between these individual components respectively digital artefacts occurs. This is realised via various interfaces to the physical but also to the virtual space (information exchange with other DTs) [11].

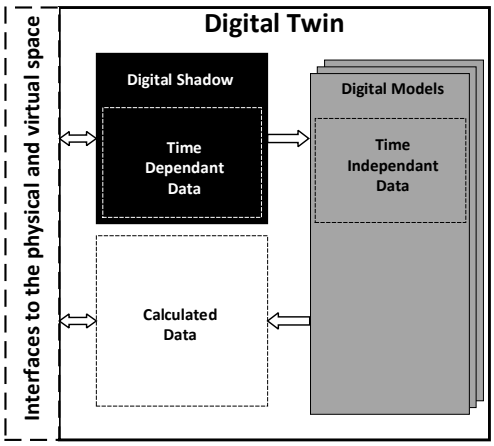

FIG. 2: DT WITH ITS DIGITAL ARTEFACTS, ACCORDING TO [11].

B. Semantic Technologies

In the era of Industry 4.0, a huge amount of data is generated that contains potentially valuable knowledge. However, solely raw data is of no use as long as no meaning is added. To obtain important information from and enable interoperability between the DT and its digital artefacts, as delineated in Sec. II, the DT must be enriched with semantics. To generate knowledge, this information must subsequently be linked by considering the relevant context [17].

Ontologies from the field of symbolic AI are a graph-based knowledge representation for the explicit specification of semantics within a domain [18]. Moreover, they are a suitable means for data management by describing information as well as its relationships to each other in a formal and machine-readable way [16, 19]. Most importantly, this facilitates the understanding of the information exchanged between the different actors managing the data for DTs [1]. ST are intended to develop and use such ontologies. For this purpose, the World Wide Web Consortium (W3C) has defined important ST standards like RDF, OWL and SWRL [18].

Various publications describe the benefits of Ontology-Based Data Integration (OBDI) and Ontology-Based Data Access (OBDA) to heterogeneous data sources, e.g. [20–22]. As such, knowledge of a domain can be formalised and contribute to the automation of partial steps in various use cases [23, 24]. In this context, Hildebrandt et al. [23] have introduced an ontology building method for Cyber-Physical systems (CPS) based on standards and norms. Beginning with an elicitation of requirements for the ontology by defining competency questions, method steps are introduced for the systematic modelling of the T-box and the A-box. The T-box describes terminological knowledge of a domain, i.e. relevant concepts and their relations. The associated A-box instantiates the T-box with different individuals, thus describing assertional knowledge [22].

III. RELATED WORKS

In Sec. III works related to the mentioned objective of this contribution will be described. On the one hand, DT approaches in the field of aviation as well as their specific use cases in different life cycle phases are considered in part *A*. On the other hand, part *B* describes the application potentials of ST for DTs in existing works and comparable domains.

A. DT in Aviation

There is a wide range of papers in the field of aviation using DTs and including digital artefacts for different applications and life cycle phases. Meyer et al. [7], for example, describe three use cases for DTs of aircraft and essential components. Firstly, a virtual product house is described, which aims to make aircraft design more efficient and cost-effective by using virtual testing and simulation-based certification. Secondly, a virtual engine is introduced in order to consider the development, design and optimisation of engine components and assemblies in varying levels of detail. Thirdly, a research aircraft with numerous DTs for various test aircraft of the German Federal Republic research centre for aeronautics and space is discussed. The superordinate result is a digital model of the aircraft and its components with all features and relevant data.

Yet other publications focus on the processes of manufacturing of aircraft components and the aircraft assembly. In [25], for example, a concept for a collaborative

workplace for aircraft assembly is presented by Mhenni et al. The authors highlight the importance to conduct as many functional and dysfunctional experiments as possible with a DT connected to the physical system so that both are improved and converged. Furthermore, the relevance of the abstraction and integration of knowledge along the entire system is emphasised. In [26] the DT provides the foundation for an effective quality management and analysis of aircraft final assembly by using data mining methods. The multi-dimensional virtual model enables DT-based quality analysis and decision-making. This lays the foundation to describe and respond to the real-time state of each quality factor, thus improving the predictability and the quality analysis.

The usability of DTs is also being researched in the area of operation and maintenance of aircraft and its components. Liu et al. [8] describe how a DT of an aircraft can be used to proactively identify potential problems with its real-world counterpart at runtime. By using a combination of physics-based models and data-driven analytics predictions can be made regarding the remaining useful life of the physical asset. In [2] a case study of DTs for aircraft maintenance is conducted by Wang et al. In this context, the DT is built to reflect aircraft maintenance, repair, overhaul (MRO) processes and activities. The increasing number of sensors combined with networked systems enable the DT system to obtain detailed information about the condition of the aircraft and its components. On this basis the future behaviour can be predicted and maintenance activities can be planned. Cloud-based technology greatly improves the affordability and availability of the computing power required to run DTs of such complex machines.

Other publications focus on a cross-life cycle or cross-organisational use of DTs in the domain. In [27] it is described by Tuegel et al. how the DT will enable better management of an aircraft throughout its lifespan. In the current aircraft life prediction process, each type of physics has its own separate model. With DT integration of material state evolution models into a single unified structural model, the physical models will be seamlessly connected, just as they are connected in the physical structure. The DT provides a visual database that is directly linked to both, the structural model and the physical aircraft. Mandolla et al. [9] outline the need for a DT of the supply chain of an additive manufacturing process in the aviation domain. The target is to ensure maximum traceability and transparency of each operation performed on a component's history to verify its conformity for certification purposes. For this purpose, the blockchain technology is used for storing data in a secure, verifiable, and permanent way.

In sum, it can be stated that there are various approaches for the potential application of DTs and generated digital artefacts in the aviation industry across different stages of an aircraft and its components. However, there are huge potentials regarding the implementation of cross-lifecycle approaches. The basis is the definition of a uniform semantic of the data by using an end-to-end information model based on domain knowledge and standards. This is intended to ensure the interoperability and reusability of created digital artefacts.

B. Semantic Technologies for Digital Twins

Data management and integration in the DT by linking various data and models throughout the product life cycle is a major challenge with regard to heterogeneous data sources and the multitude of companies involved [19, 24]. Some publications from other domains show that there is already intensive research on the application potentials of ST in DTs to overcome the challenge of isolated information silos.

Singh et al. [19] present a DT ontology by defining the conceptual knowledge required for this purpose. The ontology is classified into three main parts. The physical layer describes an asset and the associated sensors. The data layer in turn represents the sensor data and the knowledge base. The models as well as the visualisation and analysis are located in the model layer. In addition, actionable insights are introduced. The linking of all these concepts serves to represent a typical information flow in a DT. The authors of [1] describe an approach for the representation of all relevant data in a supply chain for semiconductors by means of a DT. Especially, the phases of planning, development, production and delivery are taken into account. The superordinate target is the holistic digitalisation of the product life cycle through the integration of data from participating companies. For this purpose, the supply chain with its entities (e.g. products), processes and relationships are represented by means of an ontology. This enables improved collaboration between the companies. Boschert et al. [16] also emphasise the importance of using ST in order to realise 'the next generation DT'. According to the authors such a concept is particularly characterised by the semantic linking of all relevant digital artefacts (e.g. data and simulation models) along the life cycle.

In addition to data integration, ST can also be used to realise other DT capabilities. Zheng et al. [24] for example, define vision, challenges and possibilities of a cognitive DTs. In this respect, the cognitive DT is characterised by certain properties in order to autonomously perform activities. These include, among others, autonomy, cognition and continuous further development along the life cycle. To ensure these capabilities of a cognitive DT, different digital models and data must be linked semantically. ST in this context are referred to as key enabling technologies for this purpose.

The presented publications outline that the use of ST can potentially be advantageous regarding the integration and management of digital artefacts in DTs in order to achieve interoperability. This refers to use cases that aim to integrate data within one specific life cycle phase as well as to those that take cross-life cycle approaches.

IV. Application Potentials of ST for DTs in Aviation

In the following, application potentials of ST for the use in DTs for different life cycle phases of an aircraft and its components are examined. A particular focus is being placed on the phases of aircraft design, manufacturing and maintenance. In the first step, digital artefacts to be linked are observed from products, processes and resources of the respective life cycle phase. In the second step, the application potential is extended to two cross-lifecycle use cases.

A. Aircraft Design

Aircrafts are highly complex products, due to their physical size and the number of engineering disciplines involved in their design. Apart from conventional, mechanical components, recent developments in information technology (IT) are integrated in modern aircrafts. This further increases the system complexity of the aircraft. The incorporation of DTs in early lifecycle phases, like product design, can be beneficial in many respects [14]. For example, the created DTs can be reused and extended during subsequent lifecycle phases

of manufacturing, operation or maintenance [2, 8, 16]. Also, DTs incorporated during product design, can be used to derive an appropriate manufacturing process and production system design with necessary resources. As mentioned before, a key factor that enables different users and applications to reuse the data, models and services from aircraft DTs is clear and unambiguous semantics.

In modern aircraft design, the complexity of future aircraft is often tackled by implementing Model-Based Systems Engineering (MBSE). Within the aviation industry, MBSE has been adopted early and prevails as an established practice [28]. Following this approach, the product design consists of a high-level product architecture that is decomposed into structural, functional and behavioural sub-models. In addition, these can also be refined into further sub-models. While models can theoretically be refined indefinitely, MBSE relies on formal specification languages, mostly SysML, and is often limited to architectural and static views. Complex physical behaviour, including structural, electromechanical or fluid-dynamical aspects, are not within the scope of MBSE. However, these disciplines create important artefacts to the design of an aircraft. Consequently, models describing this physical behaviour as well as architectural models should be part of the descriptive part of a DT. MBSE tools can be used for both, defining the architecture of systems and creating references to external, more detailed models. The latter is necessary if static models are not sufficient to describe certain aspects.

While simple references to models can be informational for users, implemented interfaces to these models in order to use them efficiently are needed by several applications. This requires the semantics of these models and the information they contain to be explicitly defined e.g. by using ontologies. In this context ODBI can be used to integrate data, models and services within a DT for aircraft production [29].While ontologies can be used as a meta-layer in order to integrate the components of the DT, the actual data must be exchanged to be operational. Existing OBDA approaches offer access to different data sources. Furthermore, access methods to new data sources, as MBSE data [20], are being developed and can be used for semantically enriched data exchange within a DT or between DTs.

B. Aircraft Manufacturing

Current efforts in aviation have focused on reducing fuel consumption and thus also on reducing CO_2 emissions. A major contribution to this is made by weight reduction through the use of lightweight components that are manufactured from carbon fiber composites. In addition to the established production process that uses an autoclave, an alternative, resin transfer molding (RTM), is now being considered to produce those parts due to its cost efficiency. Currently, the production of large critical components using RTM processes is still at a research stage. The quality of components produced by these processes is highly dependent on selected process parameters and requires expert knowledge and parameter monitoring [30]. Typically, only a few experts possess this implicit knowledge. Furthermore, it is not accessible, neither for other employees nor machines or control algorithms. Consequently, there is a need for approaches to formalise such implicit knowledge explicitly in order to make it available for other applications. Apart from this, information on products, their production processes and used technical resources is often only available in heterogeneous data structures. For these reasons, it is difficult to contextualise information from different sources, both manually and automatically. In order to test different parameter and material combinations and their properties, a large amount of data and knowledge must be used, which is usually stored in a decentralised system. Furthermore, simulations and models (e.g. for injection processes) are used for process and RTM tool design in order to predict performance and quality of composite components as accurately as possible. Furthermore, such digital artefacts are useful as a means to expand the existing knowledge base. However, the selection of suitable algorithms for simulation-based optimisation is not a trivial task [31].

ST, as described in Sec. II and III, are suitable to overcome these challenges. From the process DT with its knowledge base, information and inferred knowledge about composite components, process configurations and required resources can be queried centrally. This also reduces the number of different software interfaces and simplifies the entire architecture and its maintenance. The expert knowledge, formalised in the ontology also lays the basis for further AI applications. One possible application with great potential for formalised expert knowledge in a machine-readable format and process rules is the use in algorithms for process control and monitoring. This offers the possibility of predictive quality assurance by detecting process deviations in the virtual process during operation and accelerated initiation of corrective measures. Moreover, maintenance activities on the machines can also be determined and planned more precisely in advance. Statements on process and product quality can be made by recording and evaluating the quality-relevant process values. Likewise, such evaluations in combination with further plant information lead to an assessment of the resources involved, so that the transition from corrective to condition-oriented maintenance can be made. Another application potential is the use of the process DT to partially perform process engineering. Normally this task is very costly in the physical world due to long process time and expensive RTM tools. Mapping these processes in the virtual space offers many advantages. One example is the virtual commissioning, in which a wide variety of process parameters can be tested in advance in the virtual space. In addition, it is also possible to simulate different process scenarios and compare the results without the process having to exist in the physical space beforehand.

C. Aircraft Maintenance

In the field of aircraft maintenance, DTs with life cycle information, as examined in related works, can be an important support for several use cases. Especially in the field of diagnosis and predictive maintenance, there is a huge need to use various data generated from sensors during operation of the aircraft as well as from the several maintenance workshops [2]. On this data basis and by considering the relevant context, different modelling approaches (e.g. high-fidelity simulation, machine learning models), can be applied for diagnosis tasks to ensure safe operation. Furthermore, an accurate and early diagnosis can significantly improve several maintenance planning tasks. Specifically, maintenance workshops are characterised by uncertainty due to a wide variety of reasons. One major factor is the lack of information about the condition of individual components or entire systems when they have arrived in the workshop [32].

Nevertheless, the use of such DTs in the field of aircraft maintenance is far from being established. One major reason is the heterogeneous data, from flight operations as well as

from maintenance workshops. A large number of different data in a wide variety of formats and structures is collected by sensors during the aircraft operation. The same applies to the data sources from the workshop with potentially relevant information on components, the maintenance activities carried out (e.g. fault symptoms, fault causes, troubleshooting) and technical resources (e.g. test benches with series of measured values). The documentation of fault symptoms, causes and successful countermeasures, for example, is recorded in unstructured form, mostly in texts, by the technicians in different workshops. In addition, as in manufacturing, there are a large number of technicians with huge expert knowledge, which is currently not used in a formalised way. If these employees leave the company, maintenance companies run the risk of losing valuable knowledge.

In this respect, ontologies can be used for a wide variety of use cases and goals. OBDI and OBDA to different data sources on the basis of domain-specific concepts would have the advantage that diagnosis tasks could be carried out more effectively and efficiently. For example, fault classification tasks using classical sub-symbolic AI methods could benefit from added context to the data and prior knowledge in order to improve the accuracy of the results. This in turn would result in an improvement of maintenance planning, which could save costs. Furthermore, ontologies in combination with approaches from Natural Language Processing (NLP) offer the potential to make the recorded maintenance activities usable by computers. This in turn can be used to create assistance systems that support the employees in knowledge-intensive tasks. The ontology serves as a knowledge base in which various data is integrated. Furthermore, the expert knowledge could be formalised by using SWRL and subsequently be used for maintenance suggestions. ST enable to build a unified structure of the digital shadows of components, maintenance processes and technical resources in a reusable way.

D. Combination throughout the lifecycle

As described in the parts *A*, *B* and *C* of this section, a first useful step is to clearly define the semantics of a specific life cycle phase. In FIG. 3, the application potentials outlined from design (arrow 1), manufacturing (arrow 2) and maintenance (arrow 3) are visually depicted once again.

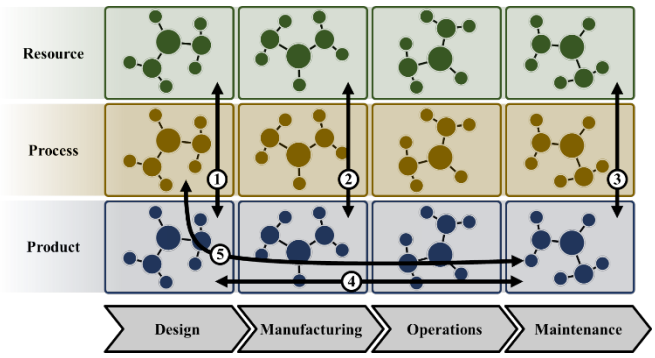

FIG. 3: APPLICATION POTENTIALS OF ST IN DIFFERENT DT LIFE CYCLE PHASES.

A particular focus in these cases, however, has been placed on the linking of digital artefacts of products (aircraft and its components), processes and resources. The ultimate goal of a DT, however, is to accompany its physical counterpart over the entire life cycle. In this contribution, the aircraft or specific individual components in particular are being accompanied. Generated digital artefacts of one phase should be reusable in different earlier or later phases. To demonstrate the added value of reusing such digital artefacts, application potentials for two further cross-lifecycle use cases are considered. Arrow 4 describes a typical application potential in the maintenance of aircraft components. For improved diagnosis, the use of high-fidelity simulation models from engineering is necessary. This allows anomalous behaviour of the component to be detected by comparing measured and calculated values. This potentially improves and accelerate the localisation of the fault causes. By semantically describing the interface to the simulation model with the required input and output variables, both data from the workshop and measured values from operation could be used even better. Moreover, there is also a great application potential the other way around as shown by arrow 5. Actually, recorded faults, fault symptoms and maintenance measures could be used retroactively in the design of components. The goal here would be to optimise the component to avoid faulty states in the operation. This in turn could have an impact on the resources and processes to be used. By using the OBDA and OBDI approaches, feasibility analyses for processes could be executed in the virtual space.

V. SUMMARY AND OUTLOOK

In this contribution, some application potentials of ST for DTs in the domain of aviation have been described. After considering related works, it has become evident that there is a considerable need for research in this area. ST are suitable for the integration and linking of different digital artefacts in a meaningful way. In this context, the phases of design, manufacturing and maintenance of aircraft, its components, resources and processes have been considered in order to identify some application potentials. Furthermore, it has been illustrated which life-cycle-spanning applications could be enabled by using ST.

Despite the application potentials shown, there is a considerable need for research in this area. A major obstacle is that individual companies along the life cycle are reluctant to hand over their data and models. Obviously, this is due to the fact that the shareholders involved are trying to protect their intellectual property. In this respect, research is needed into ideas on how such data can be offered as digital services. Furthermore, it is important to use established standards for the respective phases to formalise the domain knowledge. This should make the ontology comprehensible on a domain-wide basis and enable the reuse of models. Another problem is that many components of an aircraft are exchanged many times throughout its life. These dynamics must be synchronously modelled in virtual space, which is a major challenge in the field of research. The vertical and horizontal integration of DTs is still an open research issue that needs to be addressed. And last but not least data quality problems due to the large number of data handovers should not be neglected either. Only through a targeted and consistent digitisation of the entire process chain the full potential of the DT can be exploited.

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