Design and Implementation of Hierarchical Digital Twins in Industrial Production Environments

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Abstract

The increasing requirements for industrial production environments due to customer expectations, the implementation of batch size 1, and further automation of production processes are confronting companies with new challenges. In particular, the emergence of cyber-physical systems is influencing and complicating manufacturing processes by capturing an increasing amount of information within production facilities. Digital twins are an interdisciplinary technology that may solve these issues because they serve to monitor, control, and optimize cyber-physical systems by creating a digital representation of real-world objects. Existing concepts for digital twins usually only consider individual machines without their context. This is of limited use for production environments due to a multitude of different machines and associated sensor types. Therefore, we propose a requirements catalog, concept, and prototypical implementation for the hierarchical structuring of digital twins in this paper.

Keywords: Digital Twin, Hierarchical Digital Twin, Industry 4.0, Industrial Production Environment, Design Science Research

1. Introduction

Due to the influence of globalization and digitalization of production and logistics processes to meet challenges of the customer, cost, and time requirements, there is pressure to modernize the production processes in companies. For this purpose, production environments, especially machines, have been equipped with cyber-physical systems (CPS) to make information from the manufacturing environment available in real-time which potentially intensifies the existing problems of an adequate data presentation in industrial productions (Schuh et al., 2021). However, the mere availability of real-time data from production does not result in an appropriate presentation to the relevant groups of people, e.g., shop floor managers (Freier & Schumann, 2020; Krüger & Borsato, 2019). Digital Twins (DTs) offer an approach that has emerged in recent years in research and practice to manage, process, and aggregate the generated data, e.g., by CPS. Here, DTs reflect physical objects of the real world in digital form and enable the monitoring, control, and optimization (e.g., via simulation) of these objects via a bidirectional data connection (Glaessgen & Stargel, 2012; Negri et al., 2017). Furthermore, it is potentially possible to adjust and simulate the measures before applying them to physical objects in the real world (Vogt et al., 2021). This data connection may span across several life phases of the system (Kuehner et al., 2021).

In the context of an industrial production environment, especially concerning digitization and modernization (Industry 4.0), DTs can map machines including their CPS and the volume of generated information. DTs of machines are also able, for example, to simulate the manufacturing behavior of a machine for different products (Müller et al., 2021). Although DTs are not a new concept, previous research on this topic falls short given the high product complexity and manufacturing processes involving a large number of production sites or machines (Jiang et al., 2021; Kong et al., 2021). Concepts for single DTs are only conditionally suitable for a production environment since decision-making groups require information from different hierarchical levels of the production environment. Here, sensors, machines, production lines, factories, and companies can be mentioned from bottom to top. In addition, the interdependencies of machines in connection with the manufacturing processes of individual products must be mapped to be able to generate the integrated digital

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image of a manufacturing environment. This problem could be solved using the hierarchical structure of DTs to display a modern production environment (Jiang et al., 2021; Kong et al., 2021).

Therefore, the goal of this paper is to make a level 1 research contribution to design science according to Gregor and Hevner (2013). We follow their idea by providing requirements, a concept, and a prototype implementation of Hierarchical Digital Twins (HDT). To achieve this goal, we address two research questions:

RQ1: *Which requirements arise for hierarchically structured digital twins within industrial production?*

RQ2: *How can a prototypical implementation for the use of hierarchically structured digital twins in industrial production be designed?*

To answer these questions, the remainder of the research paper is structured as follows: In Section 2 we present the basic concepts and related research of industrial production and DTs for a common understanding. In addition, we outline the related research. In Section 3 we discuss the research method following Peffers et al. (2007), and then we present the results based on the design science research framework in Section 4. Subsequently, the discussion and conclusion of the research results follow in Section 5.

2. Theoretical Foundation and Related Research

In this section, we present the theoretical foundation of the work for a common understanding. First, the subsections outline the application domain of industrial production and the influence of digitization and modernization on this very domain in the context of Industry 4.0. Second, we discuss DTs and their hierarchical arrangement.

2.1. Industrial Production

In general, industrial production deals with the transformation of input factors into marketable material goods. This process usually takes place at a spatially defined location of a factory, using machines for this purpose (Lasi et al., 2014).

In the process, industrial production environments have become increasingly modernized and digitized. CPS, machine-to-machine communication, and extensive networking have now become part of industrial production and are covered by the term "Industry 4.0" (Freier & Schumann, 2020; Lasi et al., 2014). CPS are embedded, physical systems that integrate physical components into their environment with the help of sensors and actuators and can interact with them. In this context, network and processing functions are used to process information. Accordingly, the data generated by the machines is aggregated and processed on-site, and appropriate responses are initiated on this as a result. This is suitable for monitoring and controlling physical processes within machines of a production site (Freier & Schumann, 2020). The sensor data collected at the lowest level of production and processed on-site is particularly important because they allow a real-time response to unforeseen events (Vermesan & Friess, 2011). While this data was historically used to make control adjustments in the event of value deviations, in Industry 4.0 it is also stored to enrich other applications based on it and to receive further information from the data obtained (Lasi et al., 2014).

The hierarchical structure of a factory is described below and serves as a basis for this work. The smallest actors are CPS which operate on the bottom level with the production data. An overlying hierarchical level is a machine that comprises one or more CPS and serves to carry out individual production steps in the manufacturing process (Montreuil, 1999). If the hierarchical structure is continued, several machines are combined into a production line to define a manufacturing process of (intermediate) products. In addition, these production lines can be combined to form the factory defined above. Potentially, the hierarchical structure can also be extended upwards via further factories or even companies (Montreuil, 1999).

2.2. Digital Twin (Hierarchical)

DTs are a promising technology for resolving the challenges of complexity and the volume of information in different areas which is explained in this section. The beginnings of the concept of a DT can be found in the aerospace industry, where it was used to simulate existing flying objects as close to reality as possible (Negri et al., 2017). These simulations within a digital model are based on physical models, sensor data, and flight paths to digitally reproduce the properties and behavior of the physical model (Glaessgen & Stargel, 2012). With the emergence of the Internet of Things (IoT) and the associated availability of CPS, the concept spread to other application areas (Vogt et al., 2021). The CPS-generated information serves as the basis for the concept of a DT to bring an independent information object of a physical object into the virtual space. According to Tao, Zhang, et al. (2019), this can be implemented with three components: the physical object, the virtual mapping, and the connection between the object and the virtual mapping.

In addition to physical objects, DTs also digitally represent abstract constructs such as processes. Due to their development, DTs can reproduce complex object structures consisting of several objects. This makes it possible to simulate entire production lines or factories by having multiple DTs interact and depend on each other hierarchically (Qi et al., 2018). There is no uniform terminology for hierarchical digital twins.

2.3. Related Research

Research on the use of hierarchical structures of DTs within industrial production environments has been neglected so far. Although there are research results that consider individual, stand-alone DTs within the production environment for specific objects such as machines, there is a lack of research that considers the interaction and hierarchical structuring of these. For example, while Kong et al. (2021) describe the need for a hierarchical structure of DTs to function as needed for a production environment, they focus on the data structure needed to achieve this. This is a relevant aspect for the implementation of HDT but still falls short of providing a holistic HDT solution for the outlined problem areas in industrial production. In contrast, Jiang et al. (2021) consider the connection between physical and real objects in a hierarchical relationship with each other. The authors propose a model of such a structure and how to implement it in a production environment, although there is no validation and implementation via an application. Consequently, previous research on HDT does not consider a concrete implementation of these. Therefore, there is a need to answer our research questions.

3. Research Design

To answer the research questions from section 1, we have chosen the problem-centered design science research process according to Peffers et al. (2007) mentioned in figure 1. Our first step is problem identification, using a structured literature review according to vom Brocke et al. (2009). The main goal of this literature review is to provide a holistic overview of current approaches to (hierarchical) DTs in industrial production environments. This forms the basis for an investigation of suitability and possible adaptation. Furthermore, we can derive the goals and requirements for the design for the development of HDT (Step 2). Via the research methodology, we implemented a prototype based on the requirements (Step 3). We then conducted a demonstration with the help of an application scenario following Peffers et al. (2007) in Step 4. An evaluation study was not conducted so far and so it remains open. But still, we simulated a production environment via a script to verify that the prototype behaved as expected.

4. Hierarchical Digital Twin

In this section, we present the design of the HDT that addresses the identified research gap. In doing so, we present the requirements, design, and implementation of the HDT for industrial production in the following subsections. Similar to the structure of a DT (Section 2), the explanations within the subsections are divided into the representation, monitoring, and management of the physical and digital mapping of the target objects (Grieves & Vickers, 2017).

4.1. Problem Identification

CPS-based processing of data directly on the object, e.g., the machine, allows for faster response times in the case of unforeseen events (Section 2.1). Furthermore, the resulting information can be transferred into a DT and made available to the responsible persons and systems (Freier & Schumann, 2020; Müller et al., 2021). However, this usually only happens on a low hierarchical level, e.g., machines, of the industrial production environment. Thus, although DTs create an overview for a single object, the upward aggregated view of the information situation, from machines through production lines up to factories or even companies remains unconsidered (Kong et al., 2021).

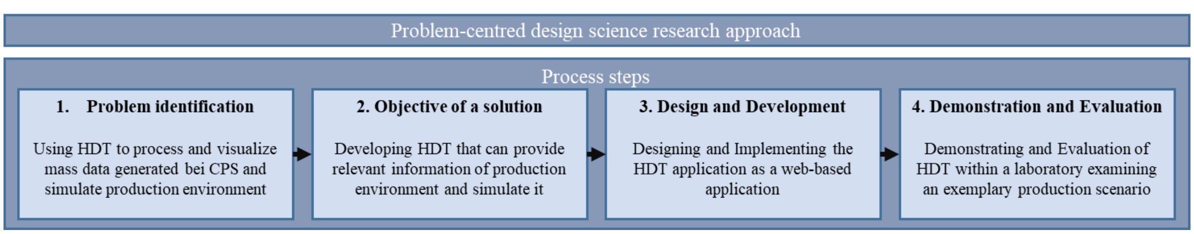

Figure 1. Research design adapted from Peffers et al. (2007)

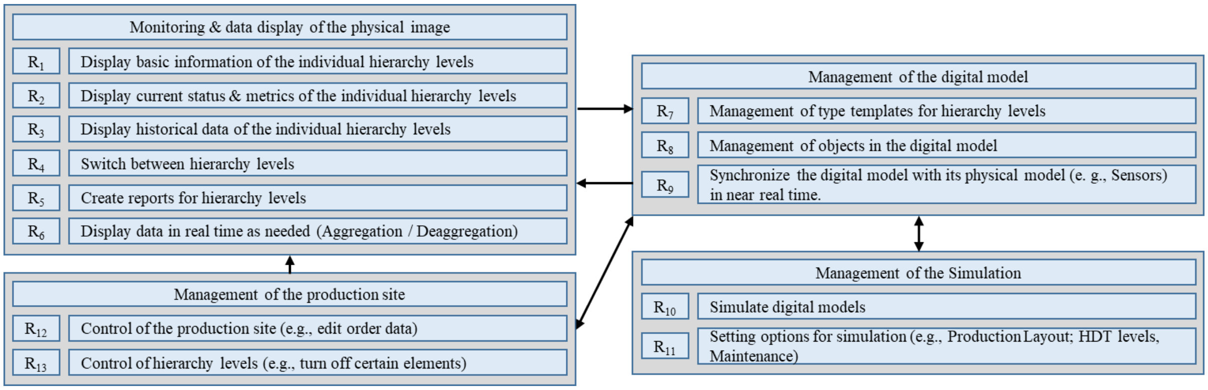

Figure 2. Functional requirements for HDT in production environments

Since DTs represent physical objects such as machines in isolation and have to map different machine specifics depending on the object, an integrated view taking into account the hierarchical structures of an industrial production environment is not possible via individual DTs. Therefore, a new DT concept integrating different hierarchical levels of a production environment is necessary. A potential benefit of these integrated DTs is a single point of information with regard to the production environment for different needs in the production environment. Different employees with different roles in a corporation have different information needs. While a machine operator on the production floor might need specific information on the current condition of the machine, a production manager might be more interested in information on the overall production flow (Autiosalo et al., 2020). A potential DT can therefore integrate sensor information of different machines and present those to relevant machine operators while also consolidating and enriching this information hierarchically and provide production metrics of the production line or the factory to managers. These metrics can be used to detect and predict failures in production. (Autiosalo et al., 2020; Schuh et al., 2020).

Thus, relevant information collected on-site is available for other activity profiles with the relevant level of depth. Furthermore, it is not only important to map the hierarchical production structure, e.g., machines, production lines, factories, in a comprehensible way, but also to be able to use the digital model of a complete production environment for simulations and, if necessary, adapt it to test alternative factory layouts. Simulations of individual DTs, e.g., of machines, can only be used effectively if they are integrated into the information situation of the rest of the production environment (Jiang et al., 2021; Kong et al., 2021).

4.2. Objectives of Solution

To solve all the above problems, we aim to develop an artifact that can represent the complex structure of a modern industrial production environment. To answer the first research question (RQ 1), we examined the existing literature for requirements on HDT in industrial production and identified about 200 atomic requirements to enable HDT. We aggregated these as part of the research methodological approach for this paper. Figure 2 shows the 13 core requirements for implementing an HDT for industrial production. The online appendix shows detailed information on the literature review conducted and the requirements table: https://lmy.de/1oGh2.
The identified core requirements can be divided into four areas (1) monitoring & data display of the physical image, (2) management of the digital model, (3) simulation functions, and (4) control functions. First, to create the data basis for the digital model, the type templates e.g., sensors and machines must be created at the beginning (R_7) (Armendia et al., 2019; Kuhn et al., 2020; Meierhofer & West, 2020; Slot & Lutters, 2021). Based on these types of templates, the actual sensors, machines, and factory layouts can then be created (R_8) (Ashtari Talkhestani et al., 2019; Brenner & Hummel, 2017; Lattanzi et al., 2021; Qi et al., 2018). Based on these types of templates, the actual sensors, machines, and factory layouts can then be created (R_8) (Ashtari Talkhestani et al., 2019; Brenner & Hummel, 2017; Lattanzi et al., 2021; Qi et al., 2018). Finally, the connection to the CPS, or physical elements such as sensors, must be established to ensure real-time synchronization of the data (R_9) (de Andrade et al., 2021; Delfino et al., 2019; Ferro et al., 2021; Shao et al., 2019). This is necessary to convert the physical object of the production environment into a digital model and thus provide the possibility to monitor it. The data thus

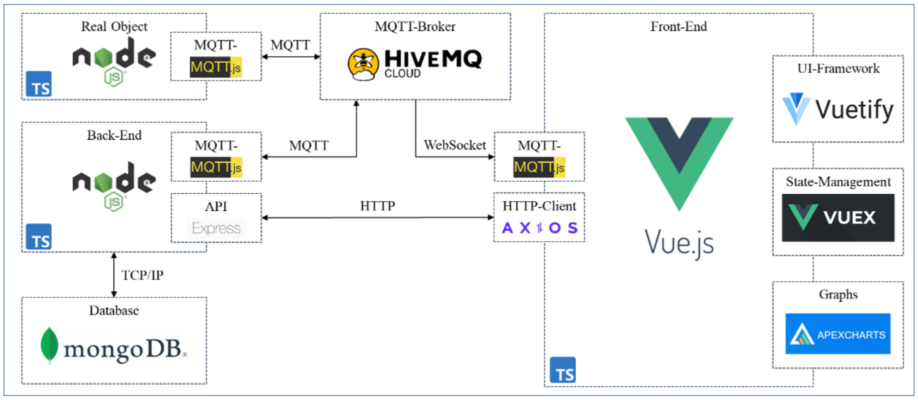

Figure 3. The architecture of the HDT Web-Application

transferred from the physical element to the connected DT can now be used to display basic information (e.g., ID, location, operating time), current status & metrics (e.g., for a machine, the current job and average processing time), and historical data in real-time (R_1; R_2; R_3; R_6) (Glatt et al., 2021; Krüger & Borsato, 2019; Kuehn, 2019; Papacharalampopoulos et al., 2021; Zhuang et al., 2018). In addition, the information prepared and displayed in this way must be displayed appropriately for the selected hierarchy level (R_4) (Jiang et al., 2021; Kong et al., 2021).

Furthermore, it should be possible to generate reports from the information (R_5) (Autiosalo et al., 2020; Rasheed et al., 2020; Schleich et al., 2019). To use the artifact, control functions are also required to manage the production environment, e.g., to create order data that can be processed (R_{12}) (Chen et al., 2018; Dalstam et al., 2018; Gericke et al., 2019). Furthermore, elements like single sensors or whole machines should be controllable, e.g., to switch them off (R_{13}) (Jain et al., 2016; Kirchhof et al., 2020; Shao & Kibira, 2018). Finally, the user can access the simulation functions to simulate the factory layout in conjunction with the order situation (R_{10}) (Davila Delgado & Oyedele, 2021; Kuehn, 2019; Negri et al., 2017). Here, the simulation environment should ensure the adaptation of the factory layout to check potential changes (R_{11}) (Heininger & Stary, 2021; Jain et al., 2016; Rolle et al., 2019).

4.3. Design and Development

To implement the stated requirements and thus solve the problem described in subsection 4.1, we have developed a web application that implements an HDT prototype. The web application allows the user to access the digital image of the hierarchically structured DTs, their information, and the associated simulation environment. Accordingly, our application consists of two components: A server that hosts the application, reads the production environment information, and contains the database, and a web component that is accessible through a web browser

Figure 3 outlines the architecture of the web application. The Node.js server simulates the physical devices in this prototype. Using the MQTT client MQTT.js, the physical devices connect to the MQTT broker HiveMQ Cloud and can receive and send messages using the MQTT protocol. The back-end runs on a Node.js server, is responsible for data processing and storage, and contains the prototype's application logic. It interfaces with the MQTT broker to receive data from the physical devices and send messages such as control commands. Connected to the back-end is the MongoDB database, which holds the prototype's data.

The Express web framework used in the back-end enables the provision of APIs through which HTTP requests can be made. The front-end uses the Vue.js framework and is responsible for presenting the data. On the one hand, the front-end requests the data from the back-end via the HTTP client Axios. On the other hand, the data comes from the MQTT broker by establishing a WebSocket connection. For data organization, the front-end uses the state management Vuex. Vuetify, as well as ApexCharts, display the data. Both the Node.js servers, on which the physical devices and the back-end run, and the front-end are implemented in the TypeScript programming language.

Figure 4 presents the core of the HDT's data model which contains four hierarchy levels (factories, machine groups, machines, and sensors). The hierarchical structure is created by assigning the elements to a parent element on the next higher hierarchy level (e.g., each machine group is assigned to exactly one factory). Sensors can be assigned to one factory, machine group or machine. Factories have no parent element as they are on the highest hierarchy level. All hierarchy levels inherit from the entity type DT-Object which contains attributes that are needed for all elements, regardless of their hierarchy level (e.g., name and location). Furthermore, machines and sensors are assigned to a specific machine type or sensor type which contains type specific attributes (e.g., the specification of temperature in degrees Celsius for temperature sensors). Some attributes are determined by data aggregation at lower hierarchy levels, where, for example, the calculation of factory utilization is done by aggregating the utilization of the assigned machine groups. The full data model of the HDT prototype, which also lists the attributes, is available in the online appendix: https://lmy.de/1oGh2. Within the full data model, the hierarchy levels (green) are expanded by the data structure for user management and maintenance (yellow), production (red), and simulation (blue).

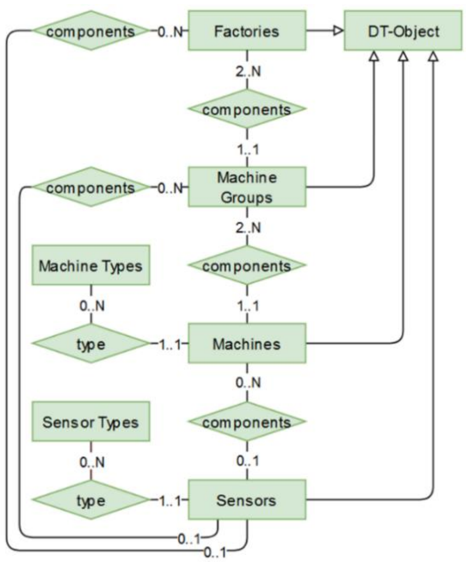

Figure 4. Data Model of the HDT

Figure 5 shows the dashboard of the HDT and the implemented data aggregation. Here, the user has a navigation bar at his disposal that allows intuitive navigation within the user interface of the application (1). The left side of the user interface shows a core element of the artifact in terms of a hierarchical structure and navigation within a production environment. This bar is expandable for navigation purposes and allows individual machines or even sensors to load their customized information views if necessary (2). In Figure 5, the top-level element is the full-scale view of second factories for the production of hand trucks. The main page shows this on the main part of the user interface, where the application displays general information on capacity and order situation (3), aggregated information about factories (e.g., current workload or the uptime of assigned components) (4), and aggregated information on machine groups (5). It is also possible to call up details for individual elements, such as machine groups, machines or sensors (6). Calling up a machine or a sensor opens a view that displays detailed information on the selected element. Opening an element on the machine group level displays information like average processing times and current throughput across all related machines and their current status by representing a larger scope of the production environment. In contrast, the machine level (Figure 6) shows a more detailed view for a specific machine and provides specific sensor values (e.g., temperature and pressure) relevant to the machine operator. The user can also view maintenance information and production history. Additionally, the HDT generates error messages, e.g., if a sensor measures values outside of the configured working range, which are displayed to a user depending on its role. The prototype is therefore capable of providing aggregated information to users depending on their individual needs and responsibilities.

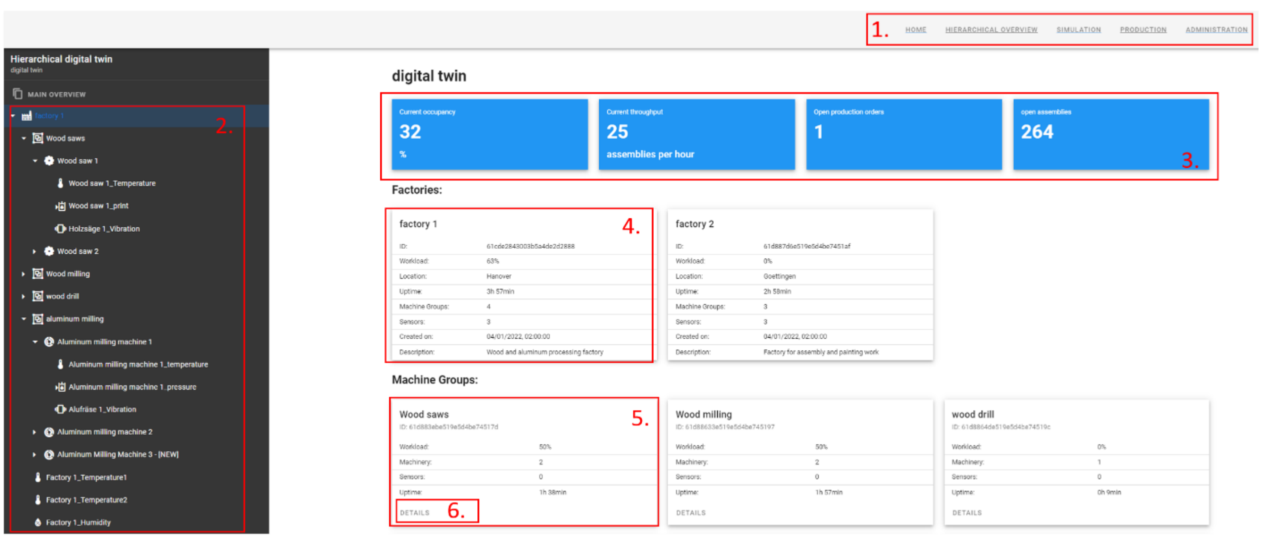

Figure 5. Dashboard of the HDT Application

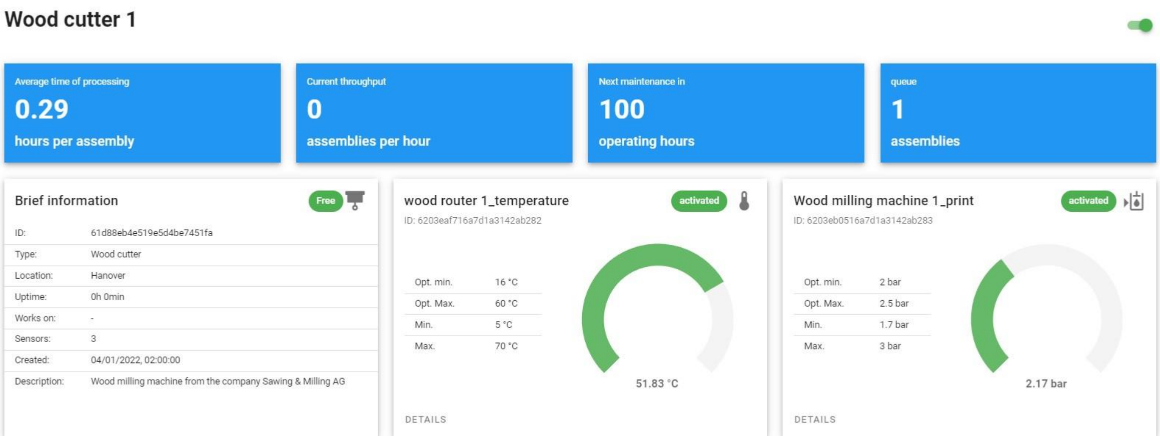

Figure 6. Overview of a machine

The simulation environment of the artifact builds on the hierarchically structured DTs, although in the context of the paper, no in-depth focus has been placed on the simulation model. The simulation model applies the first-in-first-out approach for testing purposes. This can be supplemented by other models in the future. Here, the user can specify the products to produce and adjust the layout of the production environment within several steps. If no adjustment occurs by the user, the real-world layout serves as the basis for the simulation. Subsequently, the simulation and calculation of machine loadings and total throughput time takes place to detect bottlenecks

Further information on the application is available in the online appendix: https://lmy.de/1oGh2.

4.4. Demonstration by using an application scenario

After implementing the HDT artifact for industrial production, we tested it within an application scenario. The application scenario deals with the production of hand wagons in modern industrial production in the context of CPS. With a focus on the production of hand wagons, we created an application scenario without unnecessary complexities to be able to apply and test the requirements of the HDT application areas during the implementation process.

While working with the system, the user can create jobs, and a script simulates CPS-based sensor data. Users should be able to simulate the real and potentially adapted production environment via the creation of orders and the adaptation of the virtual production environment to be able to foresee the effects of changes to the production environment. Potential maintenance work and its effects can also be considered and relevant information on the production environment is displayed to the user on a profile basis. Within the application scenario, the HDT artifact has performed according to expectations and has been verified by the project team, although an evaluation study with independent probands from the field or other suitable experts remains open and is discussed as a potential outlook. The application scenario presented can serve as the basis for a qualitative study with experts to review, evaluate, and assess the individual constructs of the HDT. Thus, we fulfilled the fourth step of the research methodological approach only partially at this point and should be covered thereafter. Further information on the application scenario is available in the online appendix: https://lmy.de/1oGh2.

5. Discussion and Conclusion

In this work, we designed and prototyped an HDT for the industrial production environment in the context of CPS, creating a design science contribution that adapts the problem-centered design science research approach of Peffers et al. (2007). By conducting a structured literature review, we identified theoretical problems. Based on this, we derived goals and generalized requirements in a literature review to realize the implementation of HDT in the industrial production environment to address these very problems (RQ1). Thereupon, we presented an HDT software artifact that enables a demand-driven presentation of the physical production environment in digital space. Furthermore, the simulation environment allows to test and adapt the models (RQ2). The prototypical implementation showed, based on the test application scenario, that the implementation of HDT within a production environment is potentially feasible. Here, the software artifact was able to display aggregated (real-time) information for each selected hierarchy level and enables switching between levels. By storing and displaying historical data, such as status data, malfunctions, or production history, the prototype can be supportive in problem analysis and identification. In addition, the user can identify optimization potentials in production, especially with the help of simulation functions. Decision-makers can test different machine configurations or new machines before applying them to reality. It is possible to identify capacity bottlenecks and eliminate them via the digital image. Furthermore, new production lines can be tested if, for example, production is to be scaled up or a new product is to be produced. Finally, the prototype is flexible and modular concerning the digital model. Users can easily add, edit, or delete objects via the corresponding management functionalities. From a scientific point of view, the requirements, design, and implementation also represent an entry point for further research on HDT design guidelines through extension, application, and evaluation of the system. For this, however, we need to further evaluate the prototype by conducting, e.g., expert interviews with practice partners and passing a further design science cycle to create a level 2 design science contribution (Gregor & Hevner, 2013). Therefore, individual constructs of the prototype should be evaluated and tested for relevance to determine if they are useful for an HDT.

However, this work has limitations concerning the structured literature analysis and the software artifact. By considering English and German literature, we have to mention that the inclusion of literature in other languages could change the results of the structured literature analysis. Furthermore, many concepts from the literature pose insufficiently specified requirements for the hierarchical structuring of DTs, which would require the derivation of specific and practice-oriented (e.g., via expert interviews) requirements. In terms of the software artifact there is no comprehensive implementation for a production environment, since intralogistics tasks within the factories have not been considered. In addition, we only tested the prototype internally with an application scenario so far, so an evaluation by experts from the field and the associated exercise testing of the theoretical approaches are still pending. In future research, we will conduct an evaluation of the requirements, concept, and prototype regarding the information presentation and simulation in a more complex application scenario taking the practical view into account. Especially the simulation environment offers the possibility to implement and evaluate different simulation strategies.

The research community should address the limitations mentioned above. More scenarios and use cases under less controlled conditions should be investigated. In these studies, we suggest mainly interviewing decision-makers within the production environment of companies via qualitative interviews to get detailed feedback on the proposed requirements as well as functions and usability of the software artifact. Nevertheless, we have developed a software solution that supports new technologies and concepts of DTs and can improve the management of enterprise production environments. However, to implement HDT in practice, a necessary step is to interconnect all elements involved in production. Infrastructure and the technical preparations on machines and sensors are required so that they can participate in the data traffic and thus use the produced data for DT functionalities.

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