Hybridization of the Digital Twin - Overcoming Implementation Challenges

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Abstract

In the context of Industry 4.0 the concept of the Digital Twin has gained significant momentum in industry as well as academia. Researchers have hypothesized a great number of potential benefits of the concept's usage. However, few real-world implementations have been recorded. This paper addresses the most pressing challenges inhibiting the concept's industrial application. It describes the process of the concept's hybridization to achieve a practical implementation strategy: the Hybrid Digital Twin. Subsequently, a prototype is implemented using a presently operational real-world manufacturing system to substantiate the viability of the methodology. Finally, the benefits, remaining issues and future developments of the concept are discussed.

Keywords: Digital Twin, hybridization, case study, manufacturing

1. Introduction

Increasing market complexities such as growing customer demands, unrelenting global competition and shortening time frames necessitate the use of innovative technologies in order for manufacturers to stay competitive (Ward et al., 2021). Especially the linkage of the physical and the digital world is an ubiquitous approach to meet these challenges. (Liu et al., 2021) Thus, an industrial paradigm change is occurring; Industry 4.0 is focusing on digital methods to address issues in modern manufacturing. In that context, the Digital Twin (DT) is one of its principal concepts (Fuller et al., 2020; Melesse et al., 2020).

A meta-review conducted by Kuehner et al. in 2021 investigated the maturity and terminology of the DT, a concept which has received considerable attention in recent years. It found that most reviewers put the concept in its infancy or at most in its growth phase. However, the terminology of the DT remains diffuse. Indeed, when using the term of the DT, different researchers seem to refer to different concepts altogether. It has been hypothesized that this is due to the "appealing metaphorical strength" (Uhlenkamp et al., 2019) of the terminology. The meta-review (Kuehner et al., 2021) also found 22 other terms that were used somewhat synonymously with the DT, contributing to the terminological indistinctness. Consequently, no universal definition has been established so far. However, based on the majority opinion of the reviewers, Kuehner et al. (2021) proposed a four point definition, which shall also define the DT for the remainder of this paper:

- DTs are virtual representations of their physical counterpart
- DTs provide the basis for simulations or are simulation models themselves
- DTs have an automated bidirectional connection with the represented physical counterpart
- this connection may span across several life phases of the physical system

The specific research gap that shall be addressed in this paper is the lack of a viable implementation strategy for DTs of manufacturing systems with real-world complexity. Therefore, the following question shall be answered: *How can one efficiently retrofit a modern manufacturing system with a Digital Twin?*

Methodically this paper can be understood as a case study that establishes a strategy for the implementation of a DT and presents an early-development prototype to show how a practical implementation could be achieved.

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It is preceded by a short narrative-style literature review that illustrates the gap in current research.

The paper will begin by elucidating typical challenges that need to be overcome in the implementation of a DT. It will then present the results of a short narrative-style literature review of DT implementations in the manufacturing domain to highlight the lack of implementation strategies for systems with real-world complexity. Afterwards, the paper will propose the process of hybridization to address most of the indicated challenges and gaps. The resulting concept will describe the fundamental ideas and strategies to establish the *Hybrid Digital Twin* (HDT). It will then introduce aspects of an early-development prototype of an operational, real-world production line to underline the adequacy of the proposed methodology. Finally, it will conclude by evaluating the progress made, the projected benefits of the HDT, the remaining issues and limitations as well as providing prospects for the future. The methodology presented in this paper will focus specifically on DTs of manufacturing systems that are already in operation.

2. Typical implementation challenges

The implementation of the DT in a real-world setting faces a number of challenges. Kuehner et al. (2021) have identified several of these challenges in their meta-review.

The most prevalent challenge was identified as shortcomings in *Data Infrastructure* (Kuehner et al., 2021). Especially for small- to medium-sized companies, real-time data acquisition might pose a problem (Melesse et al., 2020). Investments in adequate data transmission and storage technology are also crucial success factors for the implementation of a DT. Lastly, data processing capabilities need to be able to keep up with large data volumes, possibly through hardware-as-a-service infrastructures (Fuller et al., 2020).

The second most pressing challenge concerning the DT was identified as *Modelling and Simulation* (Kuehner et al., 2021). The creation of adequate models that represent the physical system in its current condition is a significant challenge in implementing a DT. A model has to mirror its physical counterpart as accurately and robustly as the intended usage of the DT requires. At the same time, models need to be able to synchronize with the physical system (see Melesse et al. (2020)) to counteract any divergence between the physical system, that will inevitably occur when both advance in time. Consequently, a model should also be able to resolve inconsistencies between the comparatively simple model and the significantly more complex physical systems (Liu et al., 2021). Additionally, inefficient simulations require more computing power, leading to higher costs. Generally, the creation of simulation models for the DT is a highly complex process. The simulation engineers need extensive domain as well as technological knowledge to build models that accurately represent the physical system. This domain knowledge may well need to span across several disciplines and technologies. Ideally, simulation models for the DT could be derived from models created in preceding life cycle phases of the system, such as 3D models, process models or even simulation models from the planning phase of the manufacturing system. In practice, such data is often not available for existing manufacturing systems.

Another pressing issue is the general lack of a universal *Concept Standardization* (Kuehner et al., 2021). As elucidated by the lack of common understanding of the terminology, the field of DTs is extremely broad and diverse. Hence, the required aspects of standardization are manifold. Principally, there is no generally accepted reference architecture for implementing the DT (Semeraro et al., 2021). However, standard data interfaces are required to supply the DT with usable data (Liu et al., 2021). Thus, standards for connecting digital and physical realms are pivotal for the development of the DT (Lim et al., 2020). Modelling guidelines spanning from initial models to the simulation design could establish domain and user understanding (Fuller et al., 2020). In the end, it is likely that the lack of standardization is inhibiting the implementation of DT concepts in an industrial context (Melesse et al., 2020).

Further issues of the DT concept identified by the meta-review (see Kuehner et al. (2021)) were a shortage of *implementation examples*, the inadequately clarified *DT benefits*, the lack of concepts concerning *Human-DT interaction* as well as possible *privacy, security and legal issues*.

All these challenges need to be addressed and eventually overcome to facilitate the advent of the DT in industry.

3. Existing implementations

This chapter presents the results of a short narrative-style review (see Ferrari (2015)) that was conducted among a selection of recent literature (published within the last five years) that self-identifies as DT implementations and has a tangible link to the domain of manufacturing. Seven publications have been evaluated on whether they were implemented in a real-world setting, were compliant with the previously established DT definition and considered systems consisting of multiple components. These points have been chosen to evaluate whether the described implementation might be transferable to real-world scenarios, which often present as complex, multi-faceted manufacturing systems. The Venn diagram in Figure 1 summarizes how these publications (S1-S7) arrange themselves among these three criteria. The publications are summarized in the following and are labelled corresponding to the diagram.

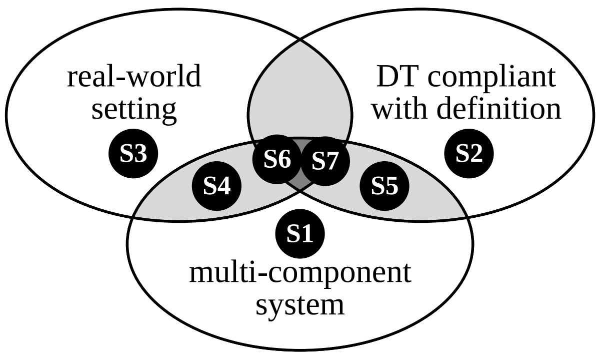

Figure 1. Venn diagram of selected case studies

Ward et al. (2021, S1) have built a DT of a multi-component manufacturing system in a laboratory at the University of Sheffield. It represents a production system consisting of machines, conveyors and robots. They employed dedicated vision and RFID sensors to attain the position of movable entities within the system and transmitted the data via standard programmable logic controllers. They could show the viability of their approach to feed data to a simulation model. However, feedback to the physical system has not been achieved.

An example for a DT of a friction stir welding machine has been developed by Roy et al. (2020, S2) in a laboratory environment. They used dedicated as well as integrated sensors to establish parameters such as oil levels, machine power, temperature and flow rates. This data was then fed into a model consisting of signal processing and machine learning elements. The model would afterwards establish maintenance operations.

An industrial implementation of a DT was performed by Aivaliotis et al. (2019, S3). They created a DT of a robot that performed welding task in a production line to assess its remaining useful life. For this purpose, they combined data from the robot's control unit with dedicated sensors assessing the acceleration of each of the robot's joints. Together with constructive data they created a simulation model to simulate the robot's components. Using this approach they were able to predict the remaining useful life of the robot's gearboxes.

Another real-world case study was performed by Biesinger et al. (2018, S4). They created a DT of a body-in-white workshop from different data sources such as planning data, simulations and dedicated 3D-scans of the physical system. Its purpose was to create an up-to-date representation of the physical system to be able to efficiently adapt it for new products. However, no operative feedback to the real system has been performed.

Researchers of the universities in Hong Kong and Shenzhen have created a DT of a multi-component manufacturing system of several assembly islands in a laboratory environment (Guo et al., 2020, S5). Its purpose was to organize the production and improve task scheduling. Data was generated via retrofitted sensors on tools, machines and other production equipment. Smart wearable equipment such as glasses, wrist-computers and belts have also been proposed. A cloud-based model organized the production sequence and instructed workers via mobile devices.

While examples for real-world implementations of a DT spanning across a whole production system are rare, Zhuang et al. (2018, S6) have achieved such an implementation in the context of a satellite assembly shopfloor. They have used RFID technology and information collected by machines or entered by operators to supply data to a digital model of the shopfloor. It then automatically supported resource management, path optimization and scheduling as well as process control and optimization.

Another example for such a system has been described by Zhang et al. (2019, S7). In a machining workshop for airplane engine parts they have created a DT which worked with the sensory data of several CNC machines to improve scheduling. Additional dedicated sensors have also been recommended. Higher production efficiencies and increased procedural transparency could be achieved.

While there clearly are several examples for DT concepts, most have yet to be transferred into real-world applications or are very limited in their scope. Even if complete production systems have been enhanced with a DT (see Zhuang et al. (2018) or Zhang et al. (2019)), they still required significant implementation efforts. Most of the seven implementations relied on additional data gathering with dedicated sensors. They also have not shown a potential to standardize their methodology to make it suitable for other applications. Consequently, this represents a gap in the research concerning DTs. It is necessary to establish a strategy that reduces the implementation effort of DTs for real-world, multi-component manufacturing systems.

4. Hybridization of the DT

As illustrated in the previous section, there is no commonly agreed upon strategy for implementing a DT for a complex real-world system. It shall be the contribution of this paper to established such a strategy: the HDT. This chapter will elucidate its derivation and introduce key components, concepts and ideas that constitute this strategy.

When investigating the definition given in section 1, it becomes clear that implementing the DT has a data side (data from the physical system must be fed into the DT) and a behavioral side (a simulation component of the DT must be able to mimic the behavior of the physical system). Further items that may be considered for implementing a DT depend on its intended usage and may include e.g. an experiment manager, a controller component for the physical system, a visualization component or a data analytics component. By combining these different concepts in the implementation of the DT, we are hybridizing it. A HDT is more than just a simulation model or just a database collecting data from the physical system. Following the definition of hybrid systems modelling (see Mustafee and Powell (2018)) we even suggest that a HDT could include multiple simulation, modelling, and analysis paradigms. In analogy to a system model becoming a hybrid system model when multiple techniques and disciplines are used, we argue that the DT becomes a HDT in the same way. Additionally, since the HDT is not merely coordinating infrastructures of different disciplines but creating new knowledge by systematically integrating them, the HDT is a step toward transdisciplinary research as described by Tolk et al. (2021).

Within the context of this paper, we discuss two approaches for finding inspiration and identifying technologies for building a HDT:

The first approach is to analyze *precursor technologies*. This means, reviewing technologies that connect physical and digital systems. Since the DT is part of the Industry 4.0 paradigm, it is fashionable and promotionally prudent to use its terminology. However, as an analysis performed by Scheer et al. (2021) has shown, there are several concepts for digital-physical connections which partly predate the DT.

Two concepts are especially relevant for the purposes of extracting valuable information for developing a DT concept. The online-simulation, a concept for a simulation which is mono-directionally connected to a physical system, is first mentioned in 1998. It could be seen as a predecessor of the DT, since it already represents a system virtually, has simulation capabilities and is connected to the physical system at least one-way, meaning in this case data flows from the physical to digital elements (Scheer et al., 2021).

The symbiotic simulation, a system of bidirectionally connected simulation and physical system, dates back to 2002. The symbiotic simulation follows the definition of the DT very closely: it represents the physical system virtually, has simulation capabilities and has a two-way data connection with the physical system, even if in some constellations a human element is required for reviewing machine decisions (Aydt et al., 2008). One could argue that most symbiotic simulations are DTs and vice versa. Therefore, it is paramount to assess and build upon research that has already been done on this subject.

The second approach to learn from previous research is to identify *existing data-related and simulation-related methodologies*.

The use of data-related technologies has a simple goal. Little to no additional infrastructure should be required to efficiently construct a DT. This directly addresses the data infrastructure challenge. Most modern manufacturing systems already collect and use data of the production systems. Consequently, data management systems as well as analysis methods are already in use. Concepts like relational or non-relational databases, real-time data streaming, data analytics, data or process mining and more sophisticated concepts such as machine learning are commonly available.

Methods based on simulation are commonly used in the context of manufacturing systems (Bergmann & Strassburger, 2010). Paradigms such as discrete event simulation (DES), agent-based modeling and System Dynamics are utilized to plan and dimension production systems. These methods are applied regularly and are commercially available in the form of specialized software (see Swain (2021) and Bergmann and Strassburger (2010)).

The goal of the hybridization of the DT is now to substitute case-specific, academically unexplored DT elements with comparatively known methods and technologies. In the end, this shall reduce the implementation effort of a DT to an economically feasible level.

Another aspect that has been part of the discussion around the DT is its comprehensiveness. However, digitally representing a physical system in great detail requires extensive effort. Therefore, the concept of the HDT focuses only on relevant aspects of a system to reduce its implementation effort. Consequently, only those facets of the physical system which are crucial for the purpose and function of the DT are represented digitally. All others are approximated or simply ignored.

4.1. Establishing DES as principal modelling paradigm

There is no universal modelling approach for creating the simulation component of the DT. The subject of a DT (e.g. a production system) has several facets and often requires multiple modeling paradigms. However, having a central paradigm and model is beneficial to later be able to integrate subordinate models. In the following we will convey our thoughts and reasoning about why DES is a suitable simulation paradigm for a DT:

DES is tried and tested for material flow simulation. Simulation is a common method in the planning process of manufacturing systems (Bergmann & Strassburger, 2010). Additionally, there are a significant number of academic resources to provide the methodological backbone of any such application (Robinson, 2005).

It is the essence of DES to be event-driven. This means that incoming information from the physical system, which is likely to be in the form of discrete information packages, can be integrated easily.

DES is also versatile. The scope of the simulation can be very diverse. Considering the manufacturing domain as an example, the scope of a DES might encompass a supply network, a supply chain, a plant, a production line, a single machine or even a single component of a machine. With the exception of computational limitations, it is possible to integrate models of a different scope almost seamlessly.

Therefore, we suggest the simulation component of a HDT to be a DES model at its core. In the implementation phase of such a model, certain design choices have to be made. On the one hand, there is the possibility of manually building up and specifying all details of a simulation model. On the other hand, it is also possible to automatically generate an up-to-date simulation model on-demand. However, this incurs significant challenges (Bergmann & Strassburger, 2010) and adds complexity to the already complex implementation procedure of a DT.

For the HDT, the most efficient path needs to be chosen to keep implementation as well as maintenance efforts to an acceptable level. We have focused on four elements of the manufacturing system to find such a path:

Firstly, there are *structural elements or fixed entities*. They encompass all elements of a system which are stationary e.g. production machines or conveyors. Since these elements are unlikely to change with a high frequency, it is sensible to manually insert this information into the simulation component of the HDT. While this will result in slightly higher maintenance cost (e.g. manually updating the model in case of change), it is likely more efficient than devising a strategy to automatically establish these elements. Automation of this process would require additional data, which in turn would have to be kept up-to-date.

Secondly, there is the *general system behaviour*. This refers to process sequences or special processes. In this instance, it is not possible to unambiguously choose automated or manual implementation. Instead, a case-by-case decision needs to be taken. If a system behaviour is likely to change frequently, an automated approach might be best. If the required process mining which establishes the information or the integration of the generated information is too complex, a manual approach might be favourable. In the end, the decision is based on the competences of the DT engineers and the manufacturing system itself.

Thirdly, *system parameters* need to be established. Parameters of a system quantify the behaviour of a system. This could refer e.g. to processing times or transfer times. These parameters do change over the lifetime of a process and sometimes have periodic elements (e.g. morning vs. night shift). Therefore, it is prudent to establish current parameters automatically. Historical data provides the empirical basis for these parameters.

Lastly, the *current appearance of the system* needs to be established. This refers to positioning of movable entities or the status of fixed entities. In any case, this process needs to be automated. Data needs to be gathered, supplied and integrated in real-time. Manual input is not possible due to this time constraint.

Using DES to create the simulation component of the DT in this way alleviates a part of the implementation challenge of *Modelling and Simulation*. A clear simulation paradigm as well as a classification for manual, semi-automatic and automatic model generation supports the implementation of the HDT.

4.2. Substituting the physical system with its digital shadow

A central question during the implementation of a DT is how the digital model can know how the physical system is currently behaving. Even if some parts of a system are fixed or at least predictable, some elements are not. In the example of a production system, the placement of equipment (e.g. machines) would be fixed, the production sequence or process parameters (e.g. process or transfer times) would be predictable to some extent. However, the placement of any movable entity (e.g. work piece carriers, automated guided vehicles, parts-in-progress) is unknown. Furthermore, the continuous manual assessment and input of such data in any sensible time frame is both impractical as well as prohibitively expensive. In the following we will elucidate our rationale of how to deal with this issue:

One way to establish this information would be to use dedicated sensors for collecting the data needed by the DT. They could be installed at relevant positions to track all moving entities and report their progress. However, there are a number of issues with this approach. Firstly, this involves the establishment of additional hardware and data infrastructure. The data has to be generated, stored as well as processed and needs to be available in a suitable form. Secondly, adequately establishing new hardware requires experience to avoid interference with productive systems and ensure correct function. DT engineers are likely to be software engineers and will probably lack the competence for these installations. Thus, an expensive interdisciplinary team would be required. Thirdly, deep domain knowledge is needed to capture all relevant data from a manufacturing system, furthering the need for an interdisciplinary team.

Another way would be to reuse the data that is already being collected. Modern manufacturing systems are typically controlled by a manufacturing execution system. These systems require exactly the same information as a DT, namely times and places of any changes within the system. If one were to access this data in near real-time, one could forego the establishment of a dedicated sensor system. However, such data collection has limitations, since information in a production system is only collected where it is needed for the execution of the manufacturing process. Consequently, in between such measurements, the status of the physical system is unknown.

In the concept of the HDT, the approach of reusing data is chosen. That means, that as long as the provided data represents the physical system accurately, DT engineers no longer need to refer to the physical system itself. All the data that has been gathered about a system in the past and is presently still being gathered constitutes its digital shadow (DS). Hence, during the development of the HDT, the physical system is substituted with its DS, since it contains the requisite details to function as the physical component of a DT. Figure 2 outlines the steps to achieve this substitution.

In practice this means that three types of data need to be either explicitly available or inferable from other data: position of all movable entities, status of all fixed entities and process parameters per interaction between fixed and movable entities. A standard information package, destined for processing in the manufacturing execution system typically contains this data, explicitly

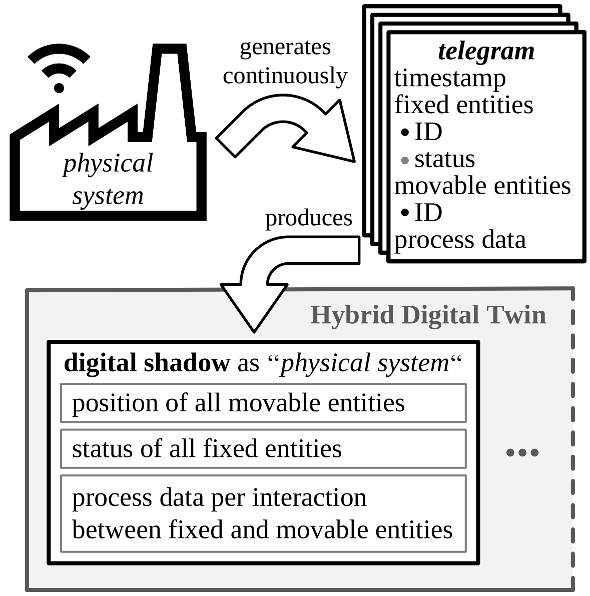

Figure 2. Physical system substituted with its DS

or implicitly. This has been visualized in Figure 2. One such information package, in remainder of this paper called telegram, should contain a timestamp, identifier of the fixed entity, the identifier of the involved movable entity, process data (if applicable) and status of the fixed entity. A system that functions this way, as most manufacturing execution systems do, enables the implementation of the HDT.

The *position of all movable entities* refers to the specific localization of any movable entity (e.g. part-in-progress). If the position of all fixed entities as well as the production sequence is known, the position of the movable entity can be inferred.

The *status of all fixed entities* can either be directly extracted from a telegram (e.g. start/end of failures) or be inferred (e.g. working normally).

The *process data per interaction between fixed and movable entity* can usually be directly extracted from a telegram. This might be the most precarious point, since a manufacturing execution system does not strictly need this information for its function and thus there is no guarantee it will be provided with it. However, a modern manufacturing system does collect data to drive process improvement, provide documentation in case of quality issues or reclamation protection as well as anomaly detection. If telegrams do not contain this data, they need to be sourced from other systems and be integrated into the HDT environment.

Real-time ingesting and processing of all telegrams with the help of data about production sequence and fixed entity positioning provides an extensive view of

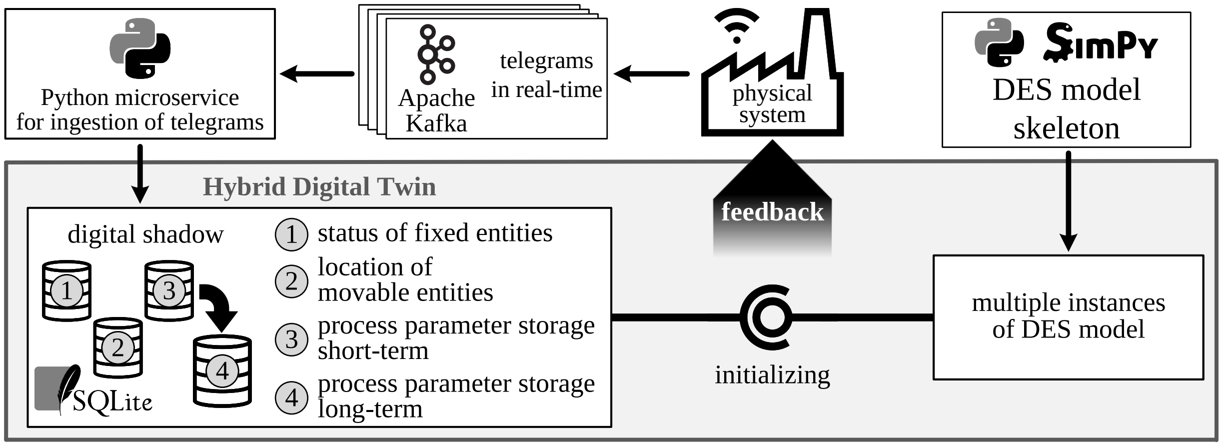

Figure 3. Schematic of the implemented HDT

the production system. Although this only provides information at certain points in time, the remaining information can be established through interpolation (e.g. analytic, simulation-based), if necessary.

Using the DS this way addresses the *Data Infrastructure* implementation challenge. Since data is already gathered, providing the DT with information is now merely a data processing issue. Additional infrastructure or data gathering instruments are no longer necessary.

4.3. Connecting DS and simulation component

At this point, the two components of the HDT have been established separately: a DES model (representing the structural and behavioural parts of the system) and the DS (containing a quantitative view of the physical system in real-time). In the following we will describe our approach to connect them:

Within the concept of the HDT a loose coupling strategy is preferred. This means that the operation of the DES model and the data ingestion into the DS are independent from each other. The use of modern databases facilitates this without the need for significant additional development. Instead, data from the physical system is continuously being ingested into databases, while simulation models can retrieve data from these databases on-demand. The database system should be able to handle issues of concurrency.

The only additional effort is to create the DES model in such a way that it can initialize itself using the data from the DS. Since a large part of the DES model has already been manually created (e.g. fixed entities and system behaviour) only system parameters and positions of movable entities have to be retrieved from the DS.

In the end, all the constituent parts of the HDT have been successfully implemented in other contexts. In many cases, commercial or mature open-source solutions are available (see Swain (2021)). This has the potential to reduce the implementation cost of the HDT sufficiently to become economically viable.

5. Prototype implementation

The test case for implementing the HDT concept is a modern manufacturing line that is assembling rotors for electric motors which are intended for use in battery electric vehicles. The manufacturing line has been in operation since 2022 in Germany. During the line's planning, engineering, construction or ramp-up phases no specific measures were taken to facilitate the integration of a DT at a later date. However, it does feature a manufacturing execution system that controls operations and also collects process data to establish traceability and to support improvement processes. In the end, its standard data collection infrastructure is compliant with the requirements of the HDT concept. It should be noted that the prototype is in early development. This means its implementation is not complete and methodical experiments have not yet been performed.

5.1. Concluded developments

The general schematic of the HDT is depicted in Figure 3. Data, which is sent to the manufacturing execution system is also supplied to Apache Kafka, an open-source event-based streaming platform. Consequently, this platform can provide a data stream which is then ingested and preprocessed by a Python-based microservice. This microservice analyzes each telegram, puts it into context with past telegrams and inserts it into the databases which constitute the DS. Two databases, in their prototypical form implemented with SQLite, represent the current status of all fixed entities and the the positioning and status of all movable entities. A third database, also implemented with SQLite, functions as a short-term memory system for all parameters concerning specific rotors-in-progress. It overflows into another database for longer-term parameter storage.

The simulation component of the HDT is a DES simulation model. The skeleton of the model, meaning representations of production hardware, production sequences and special processes, is engineered manually. The Python-based model is designed as a microservice using the open-source DES simulation package SimPy. Interfaces within the model permit the retrieval of real-time data from the databases of the DS.

In operation, a continuous synchronization between physical system and simulation model would be very demanding, since every individual physical change would immediately have to be represented in the simulation component. Consequently, potential simulations would have to be updated mid-execution to avoid working with outdated information. As the DS already provides an up-to-date view of the physical system, we argue that a periodical re-instantiating is sufficient and chose this strategy for our implementation. Additionally, the re-instantiating may also serves as part of the simulation initialization.

Long-term parameter storage provides basic system parameters such as processing times or transfer times, while short-term parameter storage shows current trends. The other two databases of the DS enable an instantiation of the model with the current status of the system. In the end, a simulation model is created that accurately represents the production line, including all parts which are in progress. Multiple instances of the model can now be simulated in parallel, providing statistically reliable results.

At this time, the implemented HDT has a range of projected applications in the production environment. Firstly, it could be used as a near real-time information system to recognize production status, anomalies and parameter drift. Secondly, the simulations from the HDT could provide a short-term prognosis of the production to identify possible issues. This way corrective measures can be implemented before any problems occur. Thirdly, the HDT could provide a testing environment for other prognostic algorithms such as machine learning, since it contains all relevant production information but has no potentially hazardous autonomous influence on the production system.

5.2. Remaining issues and proposed advancements

Since the prototype is still in early development, there are still open issues and features to be added. Further development of the HDT prototype is separated into four phases.

Firstly, methodical experimentation is required to validate results and adjust operational parameters, especially instantiation frequency, number of parallel simulations and simulated timespan. There are considerations to be made between these parameters. Figure 4 elucidates the relationship between initialization (in the prototype instantiation) frequency and simulated timespan. An extended simulation timespan will gradually lead to accumulated simulation inaccuracies due to the imperfectness of the simulation model. Reinitializing the simulation can reset these inaccuracies. However, frequent initializations lead to shortened simulation timespan, which diminishes the information gained through simulation. A suitable balance between these antagonistic parameters needs to be established on a case-by-case basis.

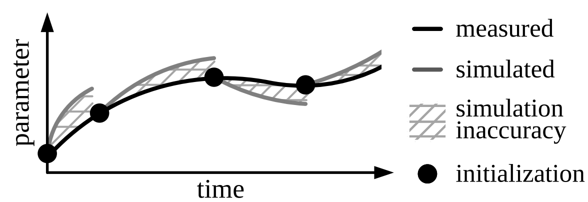

Figure 4. Principle of online-simulation, see Boh ács and Semrau (2012) and Scheer et al. (2021)

Secondly, the HDT is supposed to function as a monitoring and information system. The production line's stakeholders will be supplied with information about the current status of the system in real-time such as basic performance indicators, machine parameters and suspected anomalies (e.g. parameter drift). The development of a simple user interface and the migration of the HDT to a public cloud service will facilitate this functionality. Providing such a functionality can supply an intermediate return of expenditures toward the implementation of the HDT.

Thirdly, proactive feedback from HDT's simulations to the physical system will be established. At first, h uman a gents w ill b e n otified of is sues within the production line and will receive countermeasure recommendations. This way, all machine-made instructions have human oversight to avoid the legal and security issues of autonomous systems. At this stage, the HDT will resemble the previously researched symbiotic simulation decision support system (see Aydt et al. (2008)). In the future it is conceivable to remove operational human oversight to fully automate the system to eventually fulfil the established definition of the DT (as developed by Kuehner et al. (2021)) and of the symbiotic simulation control system (as described by Aydt et al. (2008)).

The fourth phase will encompass the extended usage of the real-time data contained within the DS and the HDT's ability to accommodate further constituent models. The HDT can be a platform to deploy simulations and algorithms (e.g. machine learning) independently from other productive systems. Since most IT systems concerning manufacturing systems are somewhat self-contained to provide security and stability, a parallel system can provide a lower-threshold alternative to develop and deploy innovative measures.

6. Summary and future work

This paper has introduced the HDT as an answer to the research question initially stated and how its main elements were derived. An early-development prototype could illustrate the feasibility of the methodology. Further, the paper could demonstrate how the most prominent DT implementation challenges can be addressed by using the concept of the HDT.

6.1. Benefits

In conclusion, the HDT is a valuable approach to introduce the concept of the DT to previously inaccessible environments due to lower implementation efforts by reducing its implementation challenges.

The main reason behind these decreased costs is the usage of well known methods. In the planning phase of a manufacturing system, decision makers and experts can efficiently gauge the cost of implementing a HDT due to its established components. There already is ample access to hardware, software as well as capable personnel to execute implementations. Consequently, the cost for this infrastructure is reasonable. Additionally, risk assessments are easier, since these known methods have equally known risks and shortcomings.

Another benefit are possible synergies that arise during the implementation of the HDT. Its individual components have independent uses. A simulation model can provide insights during planning phases even in an offline work mode. The DS can supply more systems than just the HDT with data, resulting in little to no additional cost. Data analytics and machine learning can use the exact same infrastructure. It could be argued that the connection of DS and simulation model is the only effort specific to the HDT.

6.2. Limitations

The prototype which has been described in this paper is still in early-development. Consequently, no observations, data points or testing protocols can be presented to validate the concept at this time. It is paramount to conclude the prototype's development to methodically evaluate the validity of the HDT. Furthermore, it is necessary to create additional case studies to assess the applicability of the concept to different manufacturing systems.

Even if the requirements for the HDT are comparatively low, they still limit its practicability. A manufacturing system must work with a modern manufacturing execution system. It also needs to be operational, meaning it is both currently functioning and has been functioning at least for a short while to generate data that contains information about its behaviour. It also requires at least a rudimentary data infrastructure for transmission, processing and storage of data. However, further research is unlikely to reduce these requirements.

A disadvantage of the proposed HDT concept compared to DTs which are tightly coupled to the physical system could be the potential loss of real-time control. Introducing the DS incurs certain delays which means that the HDT may no longer be able to control processes directly. However, the resulting loose coupling requires much less implementation effort and might make the implementation economically feasible. Nonetheless, the proposed setup should still prove advantageous for operative decision making.

6.3. Future development

Future developments will involve the specification and extension of the mentioned benefits as well as the continued minimization of the remaining issues. The stated goal of the HDT development is to provide a concept that is able to introduce the DT into industrial practice.

Furthermore, a dissertation will put the development and usage of the HDT in its academic context as well as provide a reference for future implementations. Thereafter, further industrial prototypes will translate the academic concept into a viable industrial strategy.

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