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Sources of Complexity in the Development of Digital Twins in Manufacturing

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Abstract. Digital twins have emerged as a critical technology to enable smart production. Digital twins can enhance the current production system by optimizing the current setup and facilitating decision-making based on facts rather than gut feeling. Despite the numerous benefits explored, digital twins have faced many challenges in developing and implementing production systems. Their complexity is causing a lack of digital twin implementations in the production system. This complexity can be traced back to physical and virtual entities and the digital twin development process. By conducting a case study in a global manufacturing company, this publication explores the sources of complexity when developing digital twins. The findings are organized around the digital twin development steps and their corresponding complexity. The number of different types of entities being modeled, the choice of the modeling approach, modeling low-frequency events, emergent phenomena, and the unpredictability and variability of the manufacturing process are all examples of structural and dynamic complexity that have been found to impede success in digital twin applications. This research has implications for managers who are involved in the development of digital twins in their organizations. It can help with methodological guidance when dealing with an undefined and complicated process of digital twin development.

Keywords. Simulation, Complexity, Smart Production, Digital Twin Modeling, Virtual Models

1. Introduction

In a competitive manufacturing environment, digital twins can assist in simulating different scenarios and testing different optimization strategies to maximize efficiency. Digital twins have emerged as a promising technology for enabling smart production to make better decisions based on data from simulations that aid in decision-making in several domains, such as production design, planning, and maintenance [1]. Digital twins

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can support sustainable production by helping with resource allocation efficiency, monitoring and reporting on progress on KPIs, and performing simulations that can quantify sustainability aspects like energy efficiency in manufacturing equipment [1, 2].

The development of digital twins is a central topic for advancing this technology and still requires more research. Previous research has highlighted an array of different problems and challenges related to the development of digital twins. In comparison with simulation models, digital twin models need to be faster, easier to use, maintainable over time, and adaptive [2-6]. Developing and maintaining digital twins is still a labor-intensive process—specifically, model creation, which might potentially be mechanized in the future [7]. For example, the developer needs to figure out how to combine data from different sources and types in a virtual model and how to choose the right level of detail for the purpose or situation. The digital twin determines the level of fidelity and detail depending on the goal [7]. Developers also need to check how the digital twin reacts in real-time settings over time and how to pick a modeling technique that best suits its purpose. Moreover, it is also important to decide how often the data from the real system should be sent to the model and what aspects of the system should be copied in the virtual world. For different applications and purposes, some aspects of the system may not be very relevant and can be left out of the model. This is where the developer needs to choose what parts and components are essential to represent its behavior. Feasible method options that propose solutions for developers to deal with these difficulties are scarce [7].

Many of the above-identified challenges are conceptually rooted in complexity. Complexity encompasses the quantity of parts within a system, the interplay among these components, and any challenges associated with predicting their interactions [8-10]. The complex digital twin's development process is unknown. The development of the digital twin integrates the ideas of holism and reductionism, and it also emphasizes that the construction of complex systems necessitates not only decomposing them into simple objects that can be implemented but also analyzing relationships among the components and considering their functions (including the system's inputs and outputs) as a whole [11, 12]. However, there is a scarcity of literature on how to develop complex digital twin models [11] and what the sources of complexity are during this process. Therefore, this paper aims to explore the specific sources of complexity in the development of digital twins in manufacturing.

2. Literature review

2.1. Development of Digital twins in manufacturing

The digital twin is a young concept with the capability of simulation first introduced by Nasa [13]. However, researchers and companies do not have a standard definition [14-17]. Digital twins have three main components: the real space, the virtual representation, and its connections [18]. The real space refers to the element being replicated; the virtual representation tries to replicate the characteristics of this object in the virtual space, and both are connected through data communication entities such as IoT and sensors. Accordingly, the digital twin can be defined as a virtual representation of elements of the production system that can be used with various simulation and analytics techniques and is distinguished by the synchronization between the virtual and physical systems, using mathematical models and near real-time data from sensors, systems and connected smart equipment [19]These characteristics and synchronization between the virtual model and physical system make it possible to visualize, monitor, analyze, predict, optimize, and simulate the performance of the production system [1].

The development of a digital twin can be divided into three main phases, namely design, modeling, and implementation [20]. The design will cover activities of objectives and functional requirements, process plan, and system requirements and architecture. The modeling phase will include determining which model will be used to build the solution, tuning and validating the model, integrating it with other models, and validating the integration. Finally, during the development or implementation phase, the synchronization with the physical production system and the security of these connections will be addressed [20].

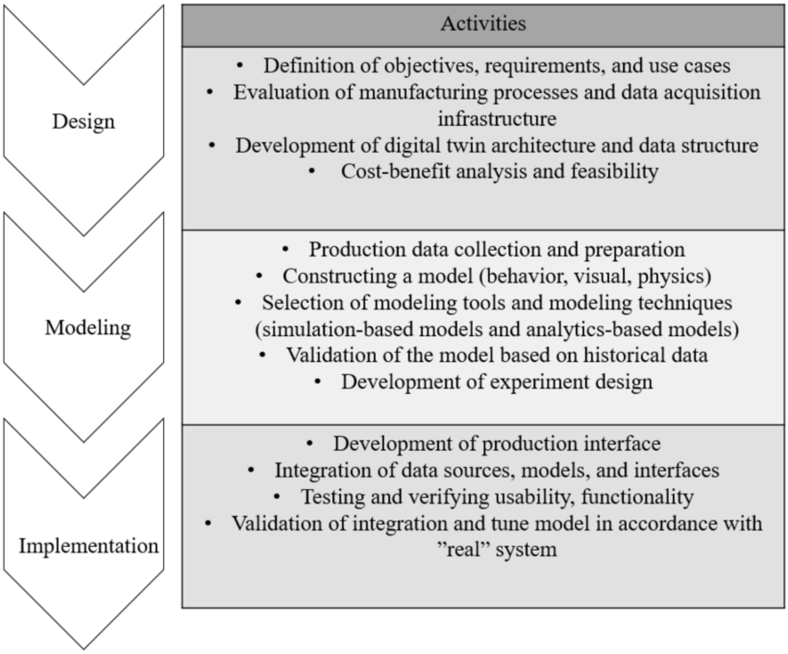

Figure 1: Digital twin development process and main activities

A DT's design is complex, with several components such as models, internal divisions, interfaces, material properties, spatial geometry, and how the entire system should be assembled [21]. This process describes the process activities and the relationships between the components that carry them out. It also decides which functionalities and system properties will be represented in the DT [20].

Data from physical and virtual shop floors is often encoded as digital twin, enables the translation of heterogeneous data into a unified information model, and uses data cleaning and fusion methods (e.g., Kalman filter, neural network, and Bayesian inference) [22]. As a result, the unified physical and virtual data become coherent and consistent, allowing a digital twin model to analyze them. Another important aspect concerning a digital twin design is a study of the cost of developing digital twins; a more detailed, higher fidelity digital twin will lead to an increased cost [23].

The fusion of several unit digital twins to create a system or shopfloor digital twin is suggested. This will entail constructing unit digital twins, assembling them together and fusing their geometrical dimension and disciplinary knowledge, model verification that ensures the accuracy of the digital twin, and model modification to address any potential deviations between the digital twin and the production system [1].

The implementation phase of digital twins requires the integration of different data sources, models, and interfaces, as well as their security [20]. One of the important aspects during this step is latency, which is the amount of time it takes for data to arrive at its destination [25]. Another important activity is the validation of these integrations and the tuning of the digital twin with the "real" system. A method for converting expert-created material flow simulation models into digital twins of production systems was developed. This method comprises converting a one-time capture of the system into a life-cycle digital twin of reality by employing real production data and automatic validation, as well as updating methods [26].

2.2. Complexity in the development of digital twins

Recent studies on the development of digital twins show the importance of dealing with complexity [11, 12]. On a general level, it is possible to divide between structural and dynamic complexity [27]. Structural complexity refers to the combination of components and subsystems into a larger system, along with their interdependence and interactions among them [27, 28]. Structural complexity poses the challenge of creating and integrating the parts, components, or variables that form a system and ensuring that they interact as intended. Dynamic complexity, on the other hand, deals with changing interactions between system components and between the system and its surroundings over time [27]. Dynamic complexity faces the challenges of adapting and learning from a changing environment. Additionally, predicting the effect of changes in the short and long term is complicated, and the intervention could change the behavior of the system. Complexity applied to models has been studied for decades, and some initial approaches suggest a relationship between the level of detail [29] and complexity or between the capacity to understand the model and complexity [30]. The lack of understanding of the real system, the inability to model correctly, or unclear modeling objectives were described as possible causes of complexity [31]. However, virtual models increased in size and complexity [32].

Later literature pointed out that there are no agreed-upon metrics for the size of virtual models and that some of the measures used were the number of process steps, number of resources, number of products, and level of interaction between process steps, entities, and variables [33]. As a result, an initial approach to measuring and classifying complexity in virtual models, which is divided into structural and software complexity, was proposed. Structural complexity is composed of the number of objects, connections, attributes, and changed and inherent attributes in the virtual model, while software complexity is composed of the total cyclomatic complexity, the total length of program codes, and computational complexity [34]. Moreover, the prevention of virtual model complexity was studied and model evolution was suggested to avoid model complexity, i.e., start with a (overly) simple model and slowly add details [35].

3. Research method

To address the purpose, this study is based on a single longitudinal case study in the manufacturing industry. Given the complex nature of digital twins, using a case study method to identify specific difficulties might be advantageous. This can aid in creating more general solutions. Furthermore, case studies contribute to in-depth comprehension, which can lead to theory formation in exploratory research [36].

The case study was undertaken at Alfa Laval, a world-leading manufacturing business in heat transfer, separation, and fluid handling technologies, with clients primarily in energy, the environment, food, and the maritime sector. This company was chosen because a company is moving forward with its digital transformation and has undertaken various internal initiatives involving digital twins in manufacturing. This case study is elaborated on a factory that frequently acts as a pilot for digitalization systems. The factory currently got the implementation of the manufacturing execution system, and more pilots planned for this factory. Therefore, more operational data is collected. The factory is interested in leveraging this operational data with digital twins. Therefore, the availability of more operational data and newer systems and the interest in the production development management in digital twins led to the selection of this case study. This case study includes the elaboration of a model that is fed with operational data in order to evaluate and improve the production system's on-time delivery. Data was collected between September 2022 and October 2023. To collect relevant data, the manufacturing execution system and its production data were analyzed, and several meetings were held with the manufacturing execution team, production development team inside the factory, related projects in data-driven solutions with a focus on enhanced data collection, a data mapping and system mapping project was completed, several meetings with software suppliers of digital twins, elaboration of a discrete event simulation model, and discussion among simulation and analytics team. Additionally, a visit to the factory was performed, a discussion of manufacturing processes and peculiarities, a discussion with production managers on more relevant factory objectives, a presentation of digital twin proposals, and the design of digital twin interfaces and connectors. The main data collection methods are described in Table 1.

Table 1: Summary of Collected Data

Methods	No.	Duration (minutes)	Types of data collected
Production Data			Production data was extracted from the shopfloor system, such as MES including team size, processing times, setup times, shifts, routes, etc.
Simulation Model			A discrete event simulation model was created with the data extracted that enabled the predict the delivery on time.
Participant observation			
Project meetings	35	60	Presentations, project status, future work
Joint learning and dissemination	7	60	Research feedback and result discussion
Factory visits	3	180	Current site status in digitalization
Informal discussions		Continually	Opinions and project activities
Documents			Production system guidelines, lean digital factory, and simulation documents

Data analysis included three concurrent activities: data condensation, data display, and drawing conclusions [37]. Data condensation is the abstraction of raw data, data display is the compression of data in visual form to draw conclusions from, and conclusions drawing is the search for the meaning of a case study in comparison with existing literature. The raw data was collected with a special focus on sources of complexity during the digital twin development. The sources of complexity collected were then coded into different groups: physical, virtual, and process-related. The data was displayed with the use of different figures and graphs and interpreted in accordance with previous literature.

4. Findings

4.1. Case Description-Discrete Event Simulation-based Digital Twin

The case study focused on the prediction of lead time and delivery dates by using a discrete event simulation approach. The sources of complexity were further investigated within this practical case of a digital twin.

The solution is aimed to be leveraged to the production shopfloor by using a low code interface application that will allow managing the production planning through different calendars, charts, and layouts. The production user may request to simulate a specific scenario. If that is the case, the application will leverage a discrete event simulation running in the background to provide an outlook on the future scenario based on the simulation results. The discrete event simulation model will be continuously updated with data provided by the manufacturing execution system, which allows it to reflect the current status of the production, therefore increasing the accuracy of the simulations produced and allowing it to immediately predict the status of the production system in the following days. The digital twin process flow is represented in Figure 2.

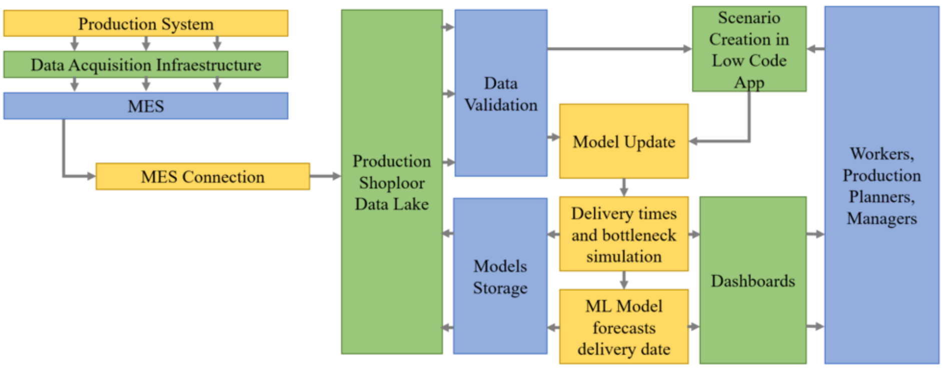

Figure 2: Illustration of digital twin proposed environment for production planning

4.2. Sources of complexity in digital twin development

In line with previous research [1, 7, 20, 38-40], the findings confirm that sources of complexity originate from the physical and virtual environment as well as the development process.

4.2.1. Physical environment-Production System

Our data reveals three sources of complexity in the physical production system:

a) **High level of interrelatedness of resources:** A key challenge was that the process of a single product cannot be modeled alone since products and stations are highly interdependent on the manufacturing processes. The manufacturing processes are organized in different areas to produce a family of components; these different areas deliver a final assembly. Many of these areas share resources and are interdependent on each other. One of the critical causes of lead times is that components from the different areas arrive at different times at the marriage point, which is the assembly area. Therefore, this interdependency of resources is critical when creating a digital twin since the manufacturing process must be represented more than partially modeling one of the areas or just focusing on one of the products.
b) **High reliance on human intervention:** A low level of automation will be a source of complexity in developing a digital twin. In this case, higher process variability is found in the data of areas with a low level of automation since process times often depend on operator skills. Additionally, the quality of data obtained for these areas is reduced compared to high automation areas since production times are wrongly reported and may include, for instance, operator breaks. A highly manual process also involves many rules unavailable to a modeler of a digital twin. In this case, for example, how the shopfloor prioritizes different orders and how products are sorted out when exiting the buffers. This implies that more data needs to be manually collected to be included in the digital twin model, and the model will need to rely on more assumptions and simplifications to deal with a low level of detail in data and to account for human factors or preferences in the production process.
c) **High rate of evolution/variation:** Another source of complexity in developing digital twins is the high number of changes in the production shopfloor. The changes affect the model, as it has to be continuously updated to reflect the current state of the system. The complexity involves finding a way to automate the change management process and visualize the impact of changes on the model and the system early on. A high number of changes also increases the effort for model maintenance and validation. For example, in this case, the team faces several layout and product changes that require modifying the digital twin model. These changes could potentially lead to many errors that could mismatch the digital twin model with the real production system.

4.2.2. Virtual environment-Digital Twin models

Our data reveals three sources of complexity in virtual environment:

a) **Multipurpose and Multiscale:** Due to the interrelatedness of various components within the manufacturing processes, the model's size extended, necessitating the creation of a larger model to achieve a more precise estimation of lead time. One of the primary difficulties encountered when working with a complex and extensive model is the prolonged runtimes, which impede obtaining prompt responses from the model and effectively debugging errors. Furthermore, this challenge became more pronounced when considering multiple objectives, as several perspectives and effects on the different objectives need to be taken into account. For instance, to improve the precision of lead time predictions, a minimum buffer dwell time was introduced before each station. However, it is worth noting that this approach had a negative impact on both resource optimization objectives and model flexibility. This is because the artificial introduction of a dwell time necessitated an increase in buffer capacity, which has an effect on buffer utilization and waiting times at the subsequent station. Hence, multipurpose digital twins are complex since modeling decisions need to evaluate the effects on both purposes. Likewise, the data shows that multiscale digital twins are also complex. The team involved in this case study comprised data engineers who specialize in working with machine learning models to predict lead times at a unit level. The data shows that integrating prediction models at a unit level into the overarching digital twin model of the system can be a source of complexity as well.

b) High Realism and Fidelity: One of the sources of complexity is the need for a high level of detail or granularity in the gathered data. Without it, it is challenging to attribute behaviors and actions to a specific timestamp. For example, this case study collected executed data about the process by track-in and track-out products. However, the activities between this track-in and track-out were not divided; transportation, breaks, processing, and setup times were all aggregated in the timestamps collected. Therefore, it is difficult to attribute specific executed times to different factors in the models. To deal with the low detail of executed data, a hybrid approach was employed, incorporating planned times derived from the enterprise resource planning (ERP) system alongside less granular actual execution times obtained from the manufacturing execution system (MES). Consequently, the availability of detailed data affects the fidelity or realism of the digital twin. The data supports that high-fidelity requirements will be linked to a higher complexity since more details need to be included in the model to predict more accurately the outcomes. One example of including more details in a model is to consider the low-frequency events that may occur in the system. For example, this case included the consideration of modeling lead times from non-recurring subcontractors, products, and re-routings should be included in the digital twin model. However, since the frequency of the events is low, there is less data about them, and it is difficult to attribute a time distribution to these events or determine how often they should be triggered, which makes them complex to be modeled.

c) **Tacit and non-measured knowledge in Models:** Tacit knowledge in the shopfloor refers to explicit knowledge and experience that they use for planning purposes. The shopfloor had some inherent rules that are domain knowledge, such as prioritization. The simulation assumes first-in, first-out buffer prioritization, but this was different from what happens on the shopfloor because the shopfloor constantly reevaluated which orders were running late and may prioritize these orders in order to meet delivery dates. However, it was difficult to model when these revaluations occurred and how the shopfloor prioritized specific orders.

4.2.3. Digital Twin Development Process

Our data reveals three sources of complexity in the digital twin development process.

a) **The ambiguous and manual development process for digital twins:** Another source of complexity in developing digital twins was the lack of a common or structured process to guide the development. This resulted in a long and uncertain time to evaluate each step and provide the necessary resources. For example, in this case, the simulation model had to run as a service on a server to communicate with the production user interface that allowed the creation of scenarios. However, the simulation engineer did not have the right certificates to install and manage the server, and there was no procedure to decide where the server should be installed and how it should communicate with other production systems. This led to several discussions and delays. Moreover, this case required a simulation engineer to spend months constructing a discrete event simulation model of the factory. The construction of the model was a highly manual and time-intensive process that depended on the modeler's experience, knowledge, and preferences.

b) Heterogenous system and data structures impede integration: One of the sources of complexity in developing digital twins was the heterogeneity of the system and data structures. The production system consisted of various systems that collected data about different parts of the equipment, such as historians, MES, and specialized systems. The production shopfloor also had different levels of digitalization within the factory. The developers of the digital twin were experts who did not have much knowledge about the local factory data and infrastructure. As a result, they faced problems such as not knowing what data these systems contained and how reliable they were, finding inconsistencies in the system, and dealing with different formats and structures of data among these systems.

c) **Deficiency of Methods to Evaluate and Refine Model with “real" System/ Deviation Threshold:** The case study aims to test the predictive capability of the digital twin model for the lead time of the most recent order for a specific product. The model will compare its predictions with the actual outcomes and report any deviations that exceed a predefined threshold. The modeler will be notified promptly of any discrepancies. This challenge is caused by the dynamic complexity of the production system, which changes frequently and unpredictably. This shows the connection and interaction between the virtual, process, and physical spaces in developing digital twins. For example, a production system with more changes and variations needs faster and more automated methods to evaluate and refine the digital twin model with the real system.

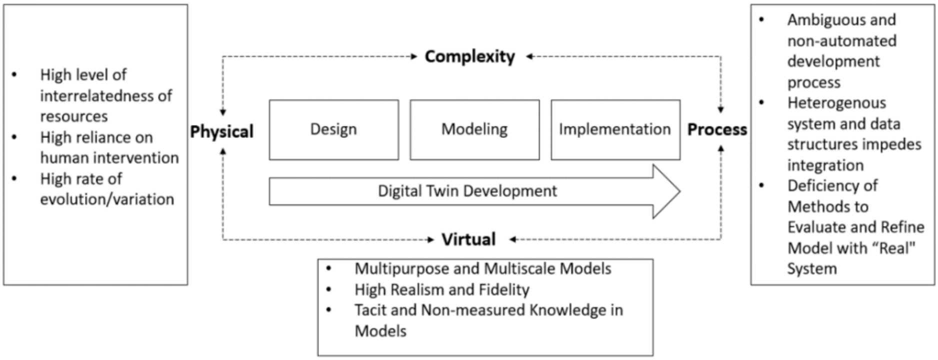

Figure 3: Sources of Complexity in Digital Twin Developments

5. Discussion and Conclusions

This paper aimed to explore the specific sources of complexity in the development of digital twins in manufacturing, as there is a lack of literature on how to develop complex digital twin models [11]. This study has three main contributions. First, it focused on the manufacturing industry, which differs from other domains where complexity has been studied before [38, 40]. Second, it identified and described three main sources of complexity and their subcategories: the physical system, the virtual model, and the creation process. Third, it analyzed how these sources of complexity are related across the physical, virtual, and process spaces. For example, a more variable and flexible production system may require a digital twin model that can adapt quickly and easily, a production environment with more human intervention may need more assumptions and simplifications in the model as data cannot be easily obtained from automation and sensors, and a model that captures a high degree of interrelatedness may increase the scale of the digital twin model as more components need to be included to understand the interactions and make holistic decisions.

The findings described different sources of complexity. The physical system that the digital twin is based on may have too many features or behaviors to be modeled accurately. Additionally, the dynamic complexity of the system with a high degree of changes and variability may be a challenge. Another is the virtual model itself, which may have many connections, interactions, and details that make it complex. Specifically, it might need to model setup times, re-routing, or advanced operator capacity in great detail. Furthermore, it needs constant calibration through time in response to physical changes. Lastly, developing the digital twin involves many decisions and choices by the developers, for instance, determining an adequate synchronization timespan, determining a modeling approach, modeling low-frequency events, and determining a specific level of accuracy required for the application. By finding out these sources of complexity, the way digital twin models are developed today can be further eased for digital twin developers.

This study has several managerial implications since it enables managers to better understand the complexity of the digital twins for their business. By identifying the source of complexity, managers can better plan the process of developing digital twins, including responsibilities and resources. Moreover, it can help managers communicate and guide developers during this process through the trade-offs and complexities of digital twin applications, such as purpose, scale, and fidelity requirements.

A possible direction for future research is to explore how to cope with the sources of complexity identified in this study. Moreover, future research could also develop and apply complexity measurements for digital twins in manufacturing that can help manufacturers assess the complexity of digital twin applications during the design process and select the most suitable use case based on these criteria.

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