School of Innovation, Design and Engineering

Assessment of how Digital Twin can be utilized in manufacturing companies to create business value

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ABSTRACT

Introduction The paradigm shift in manufacturing that Industry 4.0 brings forth with new advanced technologies and the rapid growth of sensing and controlling technologies enable further visualization and optimization that can contribute to achieving improved decision-making in manufacturing. A significant new capability is the ability to construct a Digital Twin that connects the physical and virtual space. However, there are still confusion and obscurity regarding what Digital Twin is and how it can be created and then used to create value for the company. Therefor the purpose of the thesis is to examine how manufacturing companies can utilize the implementation of Digital Twin and assess Digital Twin in a shop-floor.

- *RQ1: How can DT be beneficial to increase business value in a manufacturing company?*
- *RQ2: What changes need to be done in the shop-floor to implement Digital Twin?*

Methodology A literature review was conducted to provide previous research and context within the area of Digital Twin. A multiple-case study was performed at three case companies to gain meaningful insight from a real-world perspective, semi-structured interviews, dialogs, and observations were conducted at the case companies. The analysis was then performed by examining similarities, and dissimilarities between theoretical and empirical data, as well as opportunities in theoretical findings that correspond with challenges in empirical findings.

Frame of Reference The literature review increased the authors' understanding of the research topic and gave context to the concept of Digital Twin. The review is mainly focused on the Digital Twin technology and how it is constructed, as well as the applications areas.

Empirical Findings The empirical findings provide an overview of both the current and future state of the case companies in relation to organizational, operational, and technological factors. Additionally, it provides a deeper understanding of how shop-floor management is designed at one of the case companies.

Analysis The combination of the Frame of Reference and Empirical Findings contribute with important insight on the potential benefits that can be created through the utilization of Digital Twin, as well as what is required in the shop-floor to enable implementation of Digital Twin.

Conclusions The value that can be created utilizing Digital Twin is outlined and a clearer definition is proposed to avoid misunderstandings and confusion. Requirements that need to be achieved for a successful implementation are covered as well. A future recommendation is measuring resources and effort in relation to the created value of a Digital Twin.

Keywords: *Digital Twin, Industry 4.0, Smart manufacturing, Shop-floor Digital Twin*

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This thesis was performed during our studies in the Master Programme in Engineering within Production and Product Design. The authors' study field is innovative production and during the last semester, the focus has been in Industry 4.0. The new development is a significant challenge for manufacturing companies and a great interest for the authors on how new technologies can increase business value. With this thesis, we had the unique opportunity, with the help of our case companies, to examine this interest. Through the collection of empirical data, a profound study of literature and conversation with our helpful mentors, we were able to investigate and acquire knowledge about Digital Twin, which is an important technology in Industry 4.0.

The authors have gained valuable knowledge about the high complexity of the requirements to implement Digital Twin, which has increased the curiosity about the phenomenon. We emphasis our gratefulness to all involved companies that have received us with kindness and taken their time to help us. A special thanks to our mentors, Vincent Adoue and Moris Behnam, who with engagement and professionalism have guided and improved our thesis. Lastly, we would like to extend our gratitude to each other for the tremendous work we have put into this thesis. We could not have accomplished this without the great teamwork and support that we have shown one another.

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ABBREVIATION

CPS	Cyber-Physical System
ERP	Enterprise Resource Planning
HMI	Human-Machine Interface
PLC	Programmable Logic Controller
IoT	Internet of Thing
MES	Manufacturing Execution System
OEE	Overall Equipment Effectiveness
PDM	Product Data Management
PLM	Product Lifecycle Management

1. INTRODUCTION

This chapter will cover the overview of the background and challenges for manufacturing companies in the present where Digital Twin is described as an important technology in the coming decade. This will be addressed in this thesis through the purpose and the research questions.

1.1. Background

Due to the rapid development of advanced manufacturing electronics, information and communication technology, the production model is being transferred from digital to intelligent. This has driven modern manufacturing enterprises to change focus towards a knowledge-intensive approach (Chen, 2017; Lu, 2017). Today, it is an ongoing process to combine and integrate units to a common system, which results in increased complexity of the manufacturing process. Companies must increase the overall level of industrialisation, automation and digitalization to achieve greater efficiency, competency and competitiveness (Tao & Zhang, 2017; Xu, Xu & Li, 2018). The Third industrial revolution focuses on expanding production automation with computer numerical control, industrial robots and computer integrated manufacturing. Although, the focus in the future needs to be at a more end-to-end digitalization and integration to achieve a completely integrated solution that satisfies the demands of socialization, personalization and intelligence (Xu et al., 2018). Vertical integration is one approach that addresses issues regarding integration and connectivity among elements. It combines activities in multiple divisions to a seamless connection, thus better utilization of information- and communication technologies (Chen, 2017; Lu, 2017).

Vertical integration together with new advanced technologies within Internet of Things (IoT) and cyber-physical systems (CPS) forms the new revolution Industry 4.0. The new paradigm shift in manufacturing will provide solutions to the growing needs of information and communication in manufacturing industries (Xu et al., 2018). Industry 4.0 manufacturing is a connected information network with humans and machines that are equipped with sensors and actuators that can extract data to data-analysis technologies (Li, Tang, Wang & Liu, 2017; Negri, Macchi & Fumagalli, 2017). The connected and collaborated entities with uses of cloud computing make the physical system and the on-going processes available on the internet and thereby could utilize data science and analytical models to analyse real-time data from multiple sources (Lin, Li & Fu, 2019; Xu et al., 2018). The real-world activities can then synchronize with the virtual space, which will play an important role to enhance the two-way connection. The virtual manufacturing and environment could then work as an evaluation, verification for the physical operation to optimize and create new capabilities (Negri et al., 2017; Tao & Zhang, 2017). With the rapid growth of sensing and controlling technologies that enable new possibilities of visualization and automatization, new difficulties arise that include how to process the large range of data and how to translate it to knowledge to enhance the decision-making process in manufacturing (Chen, 2017).

A significant feature of virtual space is the capability to build “Digital Twins” that connects the physical and virtual world with its purpose of simulating different scales of time and space (Tao & Zhuang, 2017). The virtual world consists of a full lifecycle dynamic digital replica of a physical object in the real world. The Digital Twin can be constructed of physical objects from simple components, equipment to complex real-world system such as production system or the entire shop-floor at a factory (Lin et al., 2019). Digital Twin in the shop-floor consists of three components; physical shop-floor, virtual shop-floor and shop-floor service system. The integration of the Digital Twin makes the data more comprehensive and consistent which eliminates the information isolated island (Tao & Zhang, 2017). The dynamic model can fully reflect the physical object and provide operation status, insight, outcomes and knowledge (Chen, 2017). The traditional process often focuses on the collection, storage, test, process and control of data and usually loses the inconsistency between the planning and actual production. With Digital Twin that operates both in the physical and virtual space, the fused data established simulation, optimization, prediction and verification that could improve layout optimization, production planning and fault diagnosis (Tao & Zhang, 2017). However, there are some challenges associated with Digital Twin and its implementation opportunities. Initially, there is not a global definition for Digital Twin (Uhlenkamp, Hrbernik,Wellsandt & Thoben, 2019). It was first introduced by Grieves in 2004, but has since developed extensively (Tao, Zhang, Liu & Nee, 2019). Digital Twin can be built in a variety of ways with different levels of intelligence, thereby the scope of a Digital Twin may vary and leads to confusion for manufacturing companies with how it can be implemented and how it will affect current processes (Uhlenkamp et al., 2019).

1.2. Problem formulation

Digital Twin has been classified as one of the most auspicious technologies in the coming decade, despite this, there are many different understandings of what Digital Twin is since the concept is still evolving and several issues need to be addressed to increase Digital Twins' viability in practice (Kritzinger et al., 2018; Tao, Zhang et al., 2019). There are several applications for Digital Twin in manufacturing, however, there is a research gap in understanding the Digital Twin concept, framework, and development methods. This obstructs the continuing development of an authentic digital application within smart manufacturing. Some companies have applied Digital Twin in manufacturing, though there are severe restrictions within the implementation of Digital Twin (Lu, Liu, Whang, Huang & Xu, 2020). At the moment, there is no generic or unified approach on how to develop and implement the Digital Twin concept (Aivaliotisa, Georgouliasa, Arkoulia, & Makris, 2019; Tao, Zhang et al., 2019). Digital Twin can have different conceptual basis, goals, and approaches, which is a contributing factor regarding the incomprehensibility of Digital Twin. Another factor that intensifies this problem is that there is no conceptual framework that is globally acknowledged or standardized terminology for Digital Twin. Each of the Digital Twin applications is legitimate in their context, due to this a broad definition of Digital Twin becomes highly abstract and difficult to understand and imagine (Uhlenkamp et al., 2019). This transcends into other areas as well, the understanding of Digital Twin is inadequate within smart manufacturing, where the focus mainly is in the areas of product operation and maintenance (Lu et al., 2020). The reference models for Digital Twin are severely lacking (Aivaliotisa et al., 2019; Ganguli & Adhikari, 2020; Lu et al., 2020; Wagner, Schleich, Haefner, Kuhnle, Wartzack & Lanz, 2019), as well as the in-depth knowledge around research questions and challenges of Digital Twin (Lu et al., 2020).

There can be several different levels of Digital Twin depending on how complex and comprehensive it is, in literature the different types of Digital Twins are called: Digital Model, Digital Shadow, and Digital Twin (Uhlenkamp et al., 2019). The levels are also based upon the level of data integration and the different levels can be classified as subcategories of Digital Twin (Kritzinger et al., 2018). A factor that contributes to the shortfall of progress in achieving Digital Twin application is the difficulties in replicating the physical object in the virtual space (Zhuang, Liu & Xiong, 2018). To summarize the problem, the lack of a globally recognized definition and the different levels of complexity of Digital Twin creates confusion in the manufacturing industry around what a Digital Twin is, what value the implementation of it can have and what changes are necessary to enable implementation. This is a source of hesitance for investing in the technology since the manufacturing industry is highly competitive and the margin for error is increasingly low, clarity is needed if the technology is to be implemented on a higher scale than it is in the present.

1.3. Purpose and Research questions

The purpose of this thesis is to examine how manufacturing companies can utilize the implementation of Digital Twin and assess Digital Twin for a shop-floor. To achieve the purpose, it is necessary to comprehend what defines Digital Twin, important factors for successful implementation and the application areas, as well as the readiness of shop-floor processes. Therefore, the following research questions need to be answered:

- *RQ1: How can Digital Twin be beneficial to increase business value in a manufacturing company?*

- *RQ2: What requirements in the shop-floor is necessary to implement Digital Twin?*

1.4. Delimitation

The focus of this thesis will be on the Swedish manufacturing industry, where the main focal point among the three manufacturing areas will be on production, with some overlap into product design and service. The participating case companies are all global organizations that are part of the automotive- and food and processing industry. The number of participating case companies is limited to three organizations in the area of Mälardalen, Sweden. A limited number of interviews were conducted and due to restricting circumstances with social distancing in regard to COVID-19, it was not possible to conduct an observation of the production process for research question two. The depth of the thesis is affected by a set timeframe of one semester at the university and the technical knowledge of the authors, therefore the thesis is limited to theoretical and empirical findings without a proof-of-concept.

2. RESEARCH METHOD

This chapter cover description of the research approach, how the thesis was carried out and how the data was analyzed.

2.1. Research approach

This thesis used an abductive approach through combining the inductive and deductive approaches by continuously shifting between theory and empirical data where neither is prioritized above the other (Jacobsen, 2015). A qualitative study was conducted in order to focus on collecting data through semi-structured interviews (Bryman, 2008; Jacobsen, 2015). This enables nuances and interpretations that are not possible in the same manner in a quantitative study where the data is quantified in numbers instead of words (Bryman, 2008). The study is founded on knowledge gained from the authors experiences from the five years master engineer program of process and product development. Which was combined with previous research that was read to form assumptions that could be investigated via interviews with employees at manufacturing companies.

2.2. Literature review

A literature review was conducted to provide background and context of the research topic. According to Williamson (2002), the literature review involves identifying, locating and analysing the conceptual literature to find what has previously been done and where there may be a gap. The first step of the thesis was to define the problem formulation and aim of the study to limit the disciplinary field and to formulate guidelines on how to find relevant literature to the objective. Since the aim of the study has relation to Industry 4.0, the investigation was restricted to publication between 2012 and 2020. The restriction was drawn to the date that Industry 4.0 was first defined at Hannover Messe in Germany in 2011 (Jasperneit, 2012). The basis for the searches of the literature, as suggested by Williamson (2002), should be a range of literature, hence the thesis consists of theories from journal articles, conference papers and industry reports.

The main databases were Scopus since it is a citation database that can sort the articles by the highest citation. The selection of the literature was also adapted to the most recently published articles to get “state-of-the-art”-research. ScienceDirect was used as a secondary database to find relevant research outside the keywords combination. Digital Twin is a relatively new concept although similarities to the concept have emerged before, therefore a method to an inquiry was to use key articles that lead to other relevant studies when the main database publication was not available in full text. To stay within the scope of the thesis, the search of Digital Twin was combined with keywords *Industry 4.0, Technology application, classification, & Shop-floor* and is presented in table 1. Furthermore, subject area searches were limited to engineering and to exclusively English publications. This approach of the selection process is detailed by Eriksson-Barajas, Forsberg & Wengström (2013). Where the first step is to identify the area of interest and define the keywords that would be used in combination, then the criteria of how to limit the search is decided by time-period, language and area of the subject matter. The next step is to choose articles with relevant titles and read their abstracts. Of the articles that had relevant titles and abstracts for the research topic, the whole article was read. This made it possible to comprehend the specific topic and perform a quality evaluation. The literature review was further developed with the use of analyzed empirical data.

Table 1 Key articles for the literature study

Key articles	
Keywords combinations	Search results
Digital Twin & Industry 4.0	64
Digital Twin & Technology application	24
Digital Twin & classification	6
Digital Twin & Shop-floor	10

2.3. Case study

This thesis used a multiple-case study design. According to Williamson (2002), a case study is a common approach where the object of study is dynamic and not fully mature and an examination of how and why is important. The object of study in this thesis is a relatively new concept and Digital Twin did not receive much attention until 2012 (Tao, Qi, Wang & Nee, 2019). Thereby, the approach of multiple-case study was appropriate to collect data from several sources from a real-world perspective to gain meaningful insight. However, as Yin (2013) emphasizes, the analysis needs to take a larger unit into account so that the cases of interest becomes the context and not the target of the study. Hence, the cases were used to permit comparison between theoretical research and empirical data and thus be able to generalize the conclusion. According to Yin (2013), the case study could be of a holistic point of view with a focus on units or through an embedded point of view where the focus is on sub-units' analysis. To gain knowledge and insight regarding the first research question, interest was to investigate through a holistic point of view. This to get an overview of the readiness, challenges and ambition for manufacturing companies and thus to examine what value the companies can obtain with the implementation of Digital Twin. For the second research question, the data was needed from an embedded point of view to gain a deeper understanding of what is needed for the shop-floor at manufacturing companies to enable implementation of Digital Twin. Therefore, a sub-unit in one of the case companies manufacturing was analyzed to gain concrete knowledge of what is required of a production cell to implement Digital Twin.

2.3.1. Case selection

According to the aim, the focus was to examine how manufacturing companies can utilize the implementation of Digital Twin. In line with the aim, the criteria of the case company selection were that knowledge about Industry 4.0 was necessary since Digital Twin is a technology within Industry 4.0. Additional criteria were an interest in utilizing technologies associated with Industry 4.0. The case companies are part of a strong collaboration with MITC for the purpose of discussing and identifying opportunities with digitalization and Digital Twin. The respondents within each company were selected based on participation in the project and the involvement in the development towards Industry 4.0. Thus, the companies fulfill the criteria and thereby qualified as case companies where the research questions and aim were examined.

2.3.2. Data collection

The study used methods triangulation in the collection of the primary data, which implies using different data-collection methods and gathering information from several sources about the same event (Williamson, 2002). To strengthen the reliability of the collection of data, unstructured interviews, observation and dialogs were conducted with the case companies.

Interview

This thesis used a qualitative approach to investigate the phenomenon Digital Twin within the concept of Industry 4.0. Semi-structured interviews were used to examine *how* manner to gain useful information from manufacturing companies' perspective. Semi-structured interviews are designed with a set of predetermined questions that work as a question protocol. The sequence of the questions may vary at the interviews, and the interviewer can ask additional questions that are of interest or to get the answer more clearly (Bryman, 2008). For this thesis, an interviewed guide (Appendix 1 and 2) was designed before the interviews were conducted. The question protocol worked as a guideline and tool to ensure that the interviews were within the frame of the aim and the research questions. The interviewed guide contained themes from findings of the first draft of the literature review regarding important factors in the perspective of Industry 4.0. The themes were organization, operation, and technology and were then divided into sub question to grasp current state and future ambition for the case companies related to the important factors. The standardized interview guides were used for all the interviews in the purpose to perform the analysis of the questions from several perspectives. This made it possible to find similarities and differences between the case companies and the findings from the literature review. Additionally, the interviews were recorded and transcribed to improve the quality of the gathered information. Table 2 presents a description of the employees' position, the duration of the interview and the given pseudonym for each company.

Table 2 Interviews

Company	Position	Duration [min]
Argon	Manager of Operations Development	50 58*
Gallium	Manager of LEAN and Industry 4.0 Manager of Production IT	42
Vanadium	Project Manager of Smart Manufacturing	43

*= Second interview for the second research question

Observation

To increase the insight and knowledge for the cases' natural behavior and environment, Yin (2013) emphasise the importance of observation. After each interview the companies provided a guided tour of their shop-floor manufacturing to enable observation. The observation increased the understanding of what was being told during the interviews and provided the opportunity to ask further question on eventual ambiguities to gain a deeper comprehension and better connection of the reality of the manufacturing.

It would have been useful to obtain a further observation of the selected process at the case company for the second research question. However, the circumstances surrounding the current pandemic resulted in one observation and complemented documents of the shop-floor.

Dialog analysis

There have been four occasions where the authors, together with the case companies and the mentors, have gathered to discuss relevant topics concerning Digital Twin. According to Bryman (2008), the method of using dialog analysis has the purpose to capture conversations that proceed in the interaction found in naturally occurring situations. It is further mentioned that it is important to consider the prevailing context in which the conversation takes place and the constitutive nature of the social order. During the meeting, the authors had the opportunity to analyze common future demands for the case companies and important aspects that need to be highlighted related to digitalization from the manufacturing company's perspective. It was noticeable during the dialogs that there exists a mutual confusion for the case companies regarding the definition and scope of the Digital Twin. This observation shaped the thesis to the necessity of a first clarification of definition before proceeding to identify the positive effects of Digital Twin. An additional purpose of the meetings was to involve the case companies during the process to benefit from their knowledge and insight.

2.4. Data analysis

There are a variety of methods for analyzing the data in case study research. The goal of a good analysis is to obtain a high quality of data analysis where the findings are reached without predetermined perception and present evidence of alternative interpretation (Yin, 2014). The analysis of this thesis was conducted based on Collin and Hussey (2014) method of analyzing qualitative data with four elements; Comprehension, synthetization, theorization and reconceptualization. In figure 1, a visualization of the analysis process with the four elements is presented.

The first draft of the literature enabled to enrich the comprehension of the studied topic and to define the themes for the interview guide that are appropriate for the first research question. The identified important themes were *organizational*, *operational* and *technological*. These were chosen because Nwaiwu et al. (2020) highlights them as important success factors that needs to be considered and be in line with transition to smart manufacturing. By using defined themes, it facilitated the process of structuring the empirical data with colour coding related to the determine themes after careful reading through each transcript. The collected data were then compiled in Excel under the sub-categories of challenges and demands related to the themes to grasp the current challenges and future ambition for manufacturing companies. Williamsson (2014) describes that coding is a common inductive approach to analyze the case study data to identify and verify links between categories and to integrate into a theory. It this study, the sorting helped to combine elements to get a complete overview and thereby be able to synthesize a statement. It facilitated to find the relationship between the case companies by gathering all the interviews under sub-categories. It also made it easier to discard irrelevant data that was outside of the purpose and thus stay within the scope of the thesis. The same procedure of colour coding based on the themes was done on the first draft of the literature. The literature review was then developed and performed based on the outcomes from the empirical findings. Consequently, current challenges and future ambition in the empirical findings were connected to the theoretical findings regarding utilization opportunities of Digital Twin in manufacturing companies. Thereby it was possible to theorize the analysis. The authors were careful that the findings that were conducted in the analysis were of reconceptualization character. The importance of reconceptualization is due to that the theories can be at a general explanation and thereby applied to other settings. To reduce the risk of misinterpretation, the findings were discussed with the mentors who possess profound knowledge within the topic.

For analyzing the data to the second research question, the authors used the same methods from Collin and Hussey (2014) as mention before. Before the interview guide was conducted, a first draft of the literature was collected to determine appropriate themes for analyzing the second research question. With the collection of scientific articles, Tao & Zhuang (2017) was used as a basis in combination with other supporting articles for comprehending important aspects for assessment of Digital Twin in the shop-floor. The identified key areas where *shop-floor management*, *shop-floor service system* and *physical shop-floor*. Simultaneously, notes from the observation and received documentation of the shop-floor was carefully studied to determine which questions needs to be included in the interview guide to get a comprehensive insight and extensive knowledge of the process. The empirical data that had been collected and transcribed from the interview were colour coded in relation to the selected themes. With this approach it was possible to synthesize and thereby perform a process map of the current state at the case company. Once the current state was established a further development of the literature review was conducted on more detail of what is needed for the shop-floor to implement Digital Twin. By comparing the case company's process map of the current state and the literature review, the authors could theorize based on similarities and dissimilates of the findings and conduct an assessment of Digital Twin in the shop-floor.

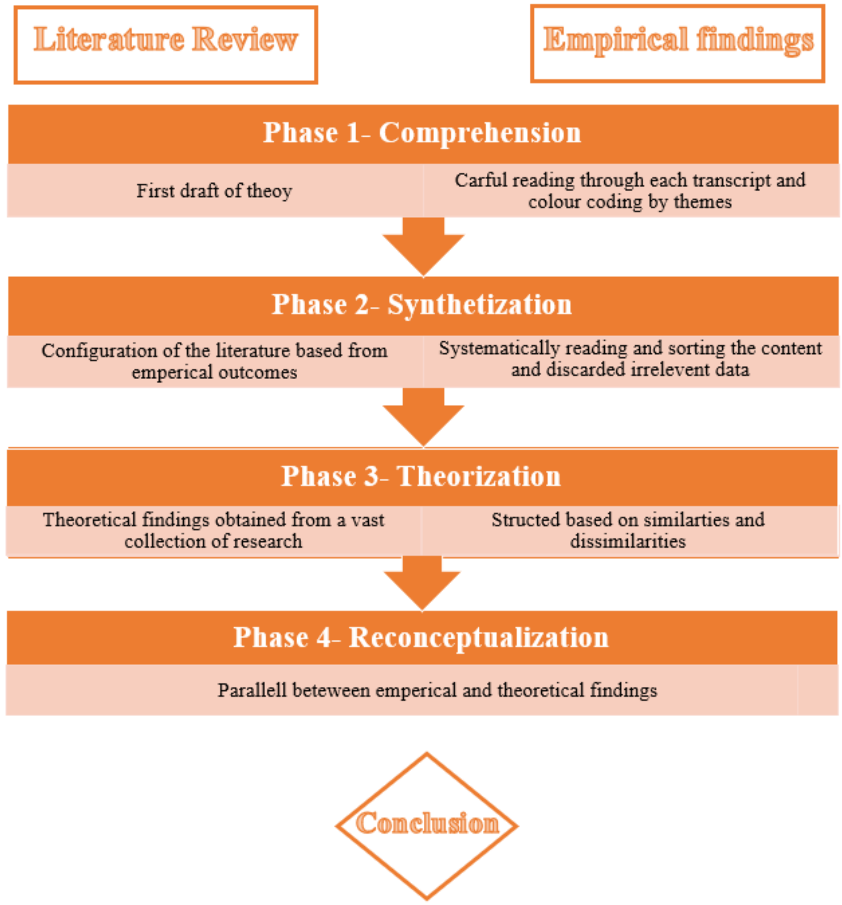

Figure 1 Illustration of research process of data analysis

2.5. Quality of research

To achieve a high-quality thesis, it is important to consider and evaluate two factors; reliability and validity (Jacobsen,2015). Reliability is further described by (Bryman, 2008) as to whether the result from a study would garner an equal result if it was performed again or if it is affected by random events and temporary conditions. The term reliability can be divided into external reliability and internal reliability. External reliability concerns whether the thesis can be replicated with the same results, which can be difficult with qualitative studies. This is mainly because it is impossible to maintain the same social- environment and conditions that exist at the start of the study. According to Jacobsen (2015), external reliability can be accomplished in qualitative studies by theoretical generalizations, this is done by discovering phenomena, determining causal mechanisms, and exposing conditions. The authors have achieved external reliability through a thoroughly structured method chapter that describes how the study has been performed through the collection of theoretical and empirical data. Theoretical generalizations have been made and the different terms used in the thesis are explained and defined to give the reader a better understanding of the subject matter. Internal reliability is achieved through a mutual understanding of the collected data by the scholars (Bryman, 2008). A consensus was reached by the authors regarding the understanding of the collected theoretical and empirical data to achieve internal reliability in the thesis.

According to Bryman (2008), validity is about whether the scholars have observed, identified, or measured what they intended to do. The term validity can be divided into internal and external validity (Bryman, 2008; Jacobsen, 2015). Internal validity is when the scholar’s observations and theoretical findings correspond (Bryman, 2008). It is also described as whether the result of a study can be considered an accurate representation of reality (Jacobsen, 2015). To achieve internal validity the authors focused on establishing interview guides with questions that would result in relevant answers to the collected theory. The questions were thoroughly scrutinized by the authors and the tutors from MITC and the university to ensure that the formulations were clear and in the right context, as well as in accordance with what information the authors wanted to gain from the interviews. External validity concerns the extent to which the results can be generalized to be applicable to other situations or social environments (Bryman, 2008). Through formulating the research questions not to be restricted to a specific company the findings can be applied to multiple manufacturing industries and are not limited to the companies that the empirical data was collected from.

3. FRAME OF REFERENCE

This chapter will begin by describing the different concepts within Industry 4.0 and how they relate to Digital Twin. Further the results of prior studies on challenges and opportunities for manufacturing companies regarding Industry 4.0 and Digital twin will be presented. This chapter will also highlight the difficulties with Digital Twin and what technology adoption is necessary for successfully implement Digital Twin.

3.1. New transformation for manufacturing companies

Digital development has led to changing demands from customers and resulted in challenges for manufacturing companies to produce products with shorter lifecycles and at a high volume of individualized products (Rasheed, San & Kvamdahl, 2020; Yin, Stecke & Li, 2018). To cope with the challenges the production needs to be flexible and responsive, which is a problem for many companies since the production system often are well-established and difficult to change (Yin et al., 2018). The growth of the new advance digital technologies has changed the condition for traditional manufacturing industries and the concepts of the new transformation are often described in similar ways and have a common goal of predictive manufacturing with proactive strategy (Lin et al., 2019; Lu, 2017; Negri et al., 2017; Zhuang et al., 2018). Table 3 shows a literature comparison of the different concepts and how they are related.

The new transformation is often referred to as Industry 4.0 and has emerged from a more complex, high demanded and knowledge-intensive manufacturing domains. This puts a higher requirement of operational efficiency and productivity (Lu, 2017). Industry 4.0 is a collection of several concepts such as Big data analytics, IoT and CPS, and together enable smart factory (Li et al., 2017; Rasheed et al, 2020; Xu et al., 2018). To become such industry, companies need to increase the overall level of industrialisation, automation and digitalization (Tao & Zhang, 2017; Xu et al., 2018). Thus, with the implantation of new technologies and connection with several devices the complexity of the system increases (Lu, 2017). The connected information network will result in an increased collaboration between machines and humans and thereby requires changes in the employees' mindset and their work tasks. New demands will be imposed in how to digitalize and manage the data, as well as how to translate the data to useful information (Chen, 2017). One of the challenges with the increased amount of data is that it is constantly being generated from different sources, at different points in time and in different formats. Software applications are often not intended to be interoperable with other systems which causes application islands and data silos. Companies need to rethink traditional digital architecture to permit new types of data-driven applications to collect the data and translate it to business advantages. Cloud computing, Big data, IoT, Machine learning, and Digital Twin are some of the latest technologies for advanced data analytics methods and algorithms that can process the high volumes of data (Lin et al., 2019). With the implementation of these technologies' factories can evolve into smart and collaborative manufacturing (Qi & Tao, 2019). An essential part to create Industry 4.0 is a smart factory with CPS that enables connectivity with manufacturing assets. The result of having the smart factory will be a fusion of technical and business processes (Xu et al., 2018).

The concept of smart manufacturing can be navigated back to 1980 but later received new attention with the new concept of "Industrial 4.0". It pursued to make the manufacturing industry into intelligent manufacturing with CPS. To realize CPS with a fusion of the physical and virtual world, real-time transmission, analysis of data and Digital Twin technology is considered as a key technology (Zhuang et al., 2018). CPS and Digital Twin are two similar concepts and therefore a demarcation between them could be problematic. The difference that can be identified between them is that CPS is akin to the scientific category due to it does not reference the implementation approaches or applications while Digital Twin is closer akin to the engineering category and used in industrial practices. Additionally, the difference between the two concepts is that CPS-architecture is focusing on computing, communication and control with sensor and actors as the core elements hence provide one-to-many correspondence (Tao, Qi et al., 2019). While the Digital Twin's core element is virtual models with data that provides similar appearance and behaviors as the physical object, thereby the bi-directional mapping between them provides co-evolving and one-to-one correspondence (Lin et al., 2017; Tao, Qi et al., 2019).

Table 3 Summery of concept related to Digital Twin

Concept	Description
Industry 4.0	Collection of several concepts e.g. Big data and analytics IoT and CPS which enables smart factory (Li et al., 2017). Industry 4.0 companies have high level of industrialisation, automation and digitalization (Tao & Zhang, 2017; Xu et al., 2018).
Smart factory	Intelligent manufacturing with CPS (Zhuang et al., 2018). Smart factory has fusion of technical and business processes (Xu et al., 2018)
Cyber-physical system	Akin to the scientific category rather than approach or application (Tao, Qi et al., 2019). Fusion of the physical and virtual world with technologies e.g. Digital Twin (Zhuang et al., 2018)
Digital Twin	Industrial technology with one-to-one component. Digital Twin consists of a virtual model and physical objects with similar appearance and same behaviors (Tao, Qi et al., 2019)

Optimal state
Predictive manufacturing with proactive strategy (Lin et al., 2019; Lu, 2017; Negri et al., 2017; Zhuang et al., 2018).

3.2. Critical success factors for smart manufacturing

To become a smart manufacturer, thus be able to use Digital Twin, it is vital to have a strategic plan on how to realize and achieve the beneficial outcomes of smart manufacturing. The company needs to develop a vision and a roadmap on how to address the future state and the several factors for successful implementation of Industry 4.0 concept (Nwaiwu, Duduci, Chromjak and Otekhile, 2020). To evaluate the maturity level for a manufacturing company within industry 4.0, there are certain methods that could be used. To visualize different maturities in levels facilitates to highlight specific steps that companies need to process towards Industry 4.0 (De Carolis, Macchi, Negri & Terzi, 2017). According to Benvenuto and Bäcklin (2019), a maturity assessment framework with five levels represent the most important steps towards Industry 4.0, where the last level represents an Industry 4.0 factory, table 4 visualizes a summarized view of what the different levels includes. Benvenuto and Bäcklin (2019) conclusion by assessing the maturity level of seven manufacturing companies in Sweden with the help of the framework, were that four of the companies had reached level 2 since the companies had either high connectivity and real-time data or had initiated the process towards vertical integration. The remaining companies were within level 1, however, possessing a roadmap was mutual for all the companies but in some cases, the roadmap was more visionary rather than practical.

Table 4 Summary of Benvenuto and Bäcklin (2019) maturity assessment framework

Maturity assessment framework		
Level 1	Initiative towards Industry 4.0	Mapping technologies and developing a roadmap that provides direction of where the company should start. Have equipment's that support digital interfaces and have an organization that involves employees in the development
Level 2	Connectivity	Increase the connectivity to achieve accessible production data and obtain competence for managing and using connected systems.
Level 3	Transparency	Initiative vertical integration and prepare for horizontal integration with real-time data and suitable IT infrastructure
Level 4	Analytics	Take advantages of collected real-time data to realize predicted physical system and extend the use of data management and analysis.
Level 5	Predictable production system	A seamless connection of vertical and horizontal integration.

The critical success factors that need to be considered and be in line with the transition to smart manufacturing are organizational, operational and technical particularities. The organizational strategy of the implementation of digital technologies needs to suitable for the processes, business units or function and encourage human resource availability and readiness. Therefore, the digitalization of the processes must be aligned with the company's strategies, capabilities and procedures (Nwaiwu et al., 2020). One of the main challenges within the organization is to create a roadmap. However, the roadmap is a necessity for the manufacturing companies to gain insight of the current state and what adjustments need to be done in specific areas (De Carolis et al., 2017). According to Lu et al. (2020), integration and interoperability are two key factors to accomplish organizational management within Industry 4.0 with a procedure that can connect components, application solutions, business processes and business context. Additionally, another important factor is to have operational knowledge of what impact digital technologies have on processes (Nwaiwu et al., 2020). To achieve smart operations, the ability of vertical and horizontal integration and end-to-end communication is necessary (Chen et al., 2017; De Carolis et al., 2017; Lu, 2017). To have a connected information network, the machines need to be equipped with smart objects to be able to perform data-analysis (Li, Tang, Wang & Liu, 2017; Negri et al., 2017). One of the challenges is to achieve a digital architecture that can translate the data into business advantages. To digitalize and process the high volume of data and create a value of it, advanced technologies such as cloud computing, Big data, IoT, machine learning and Digital Twin are needed (Lin et al., 2019). Manufacturing companies also need to plan how these digital technologies can contribute to increased competitiveness for the company and therefore technology is an essential factor that must be considered (Nwiawu et al., 2020).

3.3. Definition of Digital Twin

Grieves first introduced the concept of Digital Twin 2003 in a course on "product lifecycle management" (Tao, Zhang et al., 2019). The concept that was proposed by Grieves in 2003 was only preliminary and lacking in detail. It consisted of three parts: the physical product, virtual product, and their connections. However, the Digital Twin did not become popular until 2012 when NASA and the US Air Force began to use the concept (Tao, Qi et al., 2019). The technologies that enable Digital Twin has since then been developed extensively (Grieves, 2014). Digital Twin is described in varying ways in the literature. The absence of clarity and specification around Digital Twin elicits confusion since there is not a globally recognized definition (Ganguli & Adhikari, 2020; Hofmann & Branding, 2019; Uhlenkamp et al., 2019). Digital Twin is later described by Grieves as still consisting of the three parts and additionally the feature of close to real-time or actual real-time synchronization between the virtual and physical parts (Grieves, 2014). The collection of real-time data in Digital Twin is further supported by Glaessgen & Stargel (2012), Qi & Tao (2018), Rasheed et al. (2020), Zheng et al. (2019) and Zhuang et al. (2018). Though all definitions do not cover how the data should be collected to the Digital Twin, Guo et al. (2019), Tao, Sui et al. (2019) and Gabor et al. (2016) mention data collection but not whether the collected data is real-time data or not. According to Tao, Sui et al. (2019) the Digital Twin is capable of two-way interactions between the virtual and physical parts, this is supported by Qi & Tao (2019) and Zheng et al. (2019) as well. The varying requirements of Digital Twin is visualized in table 5, while table 6 provides an overview of the different authors perception of what defines Digital Twin.

Table 5 Requirements of Digital Twin

Author	Real-time data	Two-way interaction
Grieves (2014)	X	
Glaessgen and Stargel (2012)	X	
Qi and Tao (2018)	X	X
Rasheed et al. (2020)	X	
Zheng et al. (2019)	X	X
Zhuang et al. (2018)	X	
Guo et al. (2019)		
Tao, Sui et al. (2019)	X	X
Gabor et al. (2016)		

Table 6 Definition of Digital Twin

Author	Definition of Digital Twin
Grieves (2014)	Digital Twin consists of three components: the physical object, virtual part and their connections with real-time synchronization
Glaessgen and Stargel (2012)	Integrated multiphysics, multiscale, probabilistic highly accurate simulation that uses real time data and historical data to mirror a corresponding physical twin
Qi and Tao (2018)	Digital Twin is comprised of the physical object and a digital representation with real-time two-way mapping
Rasheed et al. (2020)	Virtual representation of a physical object based on data and simulations that enables real-time prediction
Zheng et al. (2019)	Digital Twin creates a highly accurate visualization of the physical world throughout the products life cycle with the aid of real-time and historical data, which enables the simulation of physical products realistically and interaction between the two spaces.
Zhuang et al. (2018)	Virtual dynamic model that reflects and simulates the physical entity without delay
Guo et al. (2019)	Digital mirror that maps the performance of the physical world based on extensive data that is collected from the real world
Tao, Sui et al. (2019)	Two-way interaction between a physical object and a virtual part.
Gabor et al. (2016)	High-fidelity simulation of a system based on expert knowledge and collected data from existing systems for the purpose of simulating in different scales of time and space

3.4. Intelligence level of Digital Twin

There are different intelligence levels of Digital Twin which contribute to the increased impenetrability of the Digital Twin landscape and their different dimensions (Kritzinger et al., 2018). However, there is a lack of concepts that covers the development and implementation areas for the Digital Twin (Aivaliotsa et al., 2019). One approach to divide the concept of Digital Twin is by distinguishing the different levels of data integration of a Digital Twin. The data integration between the physical and virtual models can be divided into three levels. The different levels represent the various intelligence of Digital Twin and its interconnected virtual model, as shown in figure 2 (Kritzinger et al., 2018). To determine the Digital Twin's intelligence level depending on the contained characteristics from the real system in the virtual model is difficult due to how a "good model" is defined. It could either be by distinguishing the authenticity of the real system or by the number of elements and interaction of the modelled system that exists in the virtual model.

With an increased intelligence of the Digital Twin, the complexity of the virtual model increases as more elements and interaction of the modelled system can be included (Uhlenkamp et al., 2019).

Level 1

The lowest level of Digital Twin is when the virtual model simulates the physical object but does not exchange any automated data. This can be described as a Digital Model with a virtual model that only contains a description of the physical object and are not operable to have effects on changes for the physical or digital object, thus used as a tool for assumed situations (Kritzinger et al., 2018) and Uhlenkamp et al. (2019) refer to this level as information acquisition, which can pass the information from sensors and working memory to the Digital Twin for its purpose to observe the physical object. While Lu et al. (2020) argue that a Digital Model that does not generate real-time data from the physical object should be defined as a simulation. The lack of real-time data from sensors lead to an asynchronization between the physical object and Digital Model and therefore is not consistent and cannot be described as a Digital Twin (Tao, Sui et al., 2019). The data integration is manually handled and could work as a structured information source to ensure the digital continuity of data generated from different lifecycle phases of the production system or subsystem. The Digital Twin can sense, record and communicate the manually received input data from measurement sources (Negri et al., 2017).

Level 2

Digital Twin could be described as a Digital Shadow of the physical object's entire lifecycle. The virtual model is then connected to the physical object with one-way real-time data and can react to changes in the physical object (Kritzinger et al., 2018). The virtual model in Digital Shadow could be based on different modelling approaches, such as physical and data driven. The physical approach consists of observing a physical system, developing an understanding of it and using mathematical equations to find a solution. The virtual model with modelled elements from the physical can visualize the result and thereby make it possible to streamline the workflow. The data-driven modelling is based on the assumption of data of both known and unknown physics. Algorithms are used to detect and fill the missing data and by adding smart data analysis with Machine learning and AI in the virtual model, the Digital Shadow can perform tasks without being explicitly programmed (Rasheed et al., 2020). The data from the elements could be continuously collected from the object's lifecycle so that the Digital Shadow has knowledge regarding long-term behaviors, hence predict the objects performance and other events that may affect the object. The data could be collected from the physical object regarding irregularities, fatigue and crack path and thereby be able to predict failures to improve maintenance and planning activities. With this level of intelligence, various synergistic effects can be considered and use the simulation methods and tools for multi-disciplinary of the physical system (Negri et al., 2017).

Level 3

The Digital Twin can be a seamless connection of the CPS to the digital world (Negri et al., 2017). The real-time data is integrated into both directions so that automatic data flow contributes to the control of both the physical and virtual models (Kritzinger et al., 2018). The system gets real-time synchronized with updates from the huge amount of field data. The highly intelligent Digital Twin can facilitate decision making for optimizing the different phases of the system with statistical analyses. With knowledge from the past and information from sensors of the current state, it is possible to predict and optimize future performances (Negri et al., 2017). The complexity of the virtual model can increase with the two-way connected system and act as computational models with Big data, high-fidelity simulation and AI integration. By continuously monitoring the physical object and comparing it against a reference point, the Digital Twin can be taught to be alerted when differences appear. It could then provide feedback with an error signal which generates a system input and the object can then be changed towards the reference point (Rasheed et al., 2020). This provides the intelligent Digital Twin to detect changes and important patterns with self-adaptation and self-parameterization capabilities (Uhlenkamp et al., 2019). The Digital Twin can enhance or replace a selection based on the capability of putting the analysis output into a context with high-value alternative or requirements and constraints (Barricelli, Casiraghi & Fogli, 2019; Rasheed et al., 2020).

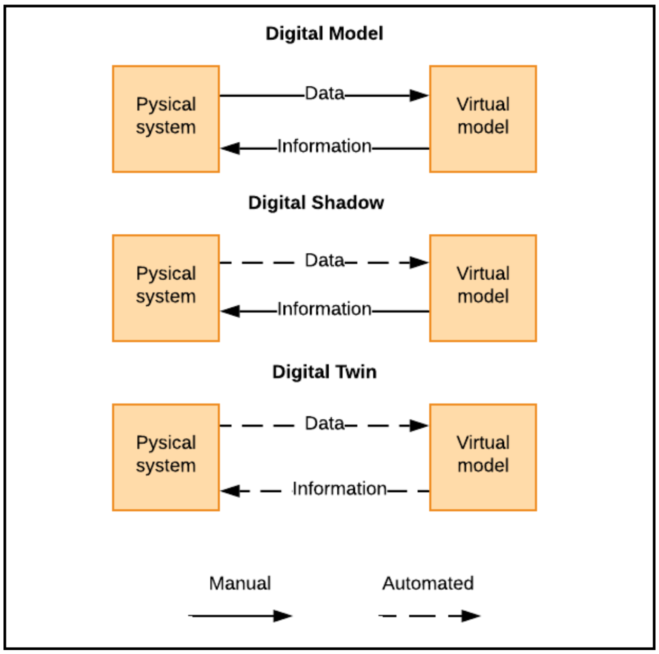

Figure 2 Data integration

3.5. Applications for Digital Twin

Digital Twin can be used in a variety of ways and different disciplines, hence the difference of the application depending on their conceptual basis, goals and approaches (Kritzinger et al., 2018). Digital Twin in manufacturing enables the creation of a highly accurate simulation and visualization of a manufacturing process and creates the opportunity to optimize the production system, as well as the logistical aspects (Kritzinger et al., 2018). Digital Twin technology encourages several different areas where the objective often is to increase competitiveness, productivity, and efficiency (Rosen, Von Wichert, Lo & Bettenhausen, 2015). The different areas of interest within manufacturing are often manufacturing assets, people, factories, and production networks (Lu et al., 2020).

The basic function of Digital Twin is the ability to act as an information acquisition by observing and receiving input data from the physical system in manufacturing (Uhlenkamp et al., 2019). The collection of data from different sources enables improved production planning and control since the statistical assumption can support decisions regarding plan offers and orders. Planning and execution of orders from the production units can transpire automatically with aid from a simulation in combination with the visualization and comprehensive diagnosis of process data (Rosen et al., 2015). An additional application of using Digital Twin's capability on information acquisition is to increase the understanding of employees' wellbeing and conditions. A linkage between the skills and demands that the employees and the technical system are under can be used to establish a strategy over how humans and machines should collaborate (Graessler & Poehler 2018; Lu et al., 2020; Wagner et al., 2019). This provides the possibility to create virtual training programs for the employees which can lead to resource optimization and higher operational efficiency (Lu et al., 2020).

Another application area for the Digital Twin is to function as information analysis. The Digital Twin can process the incoming data from different input sources to valuable information by using algorithms (Uhlenkamp et al., 2018). By transmitting real-time data from different sources, such as manufacturing assets, people, and services, the entire business can be virtually replicated (Lu et al., 2020). If several Digital Twins are used across multiple companies, the connected production network with available information combined with automated reporting will help keep the stakeholders informed and thereby improving transparency and communication. The connected production network could also facilitate to satisfy the demand of customized products and services since the detailed historical requirements, preference of various stakeholders and evolving market trends can be shared with the Digital Twins (Rasheed et al., 2020).

The Digital Twin's capability of information analysis from the fused data between the virtual and physical world can also contribute to accomplishing fully control over the product's entire lifecycle (Liu, Zhang, Leng & Chen., 2019; Wang, Wang, Yang, Zhu & Liu, 2020; Zheng et al., 2019). The Digital Twin can predict the performance of multiple designs with real-time data from the physical system to the virtual model hence provide useful information to optimize performances and thereby the manufacturing can be less reliant on physical testing (Liu et al., 2019). The prediction of how products will perform can also lead to a higher consistency of product specifications and requirements (Zheng et al., 2019). The collection of real-time data from the physical system to the virtual model also gives rise to the manufacturers to gain a clear understanding of the performance and operation conditions of the asset. By having a clear picture of the performance and condition of the asset, the situational awareness is increased and the resilience and flexibility of the operation that the manufacturing asset is working in can be enhanced (Lu et al. 2020). It can be of use in the context of mass personalization that exists in the manufacturing industry today (Liu et al., 2019; Lu et al., 2020). It also allows for a self-organizing environment with increased flexibility and operational transparency, which facilitates the optimization of manufacturing processes. This is further explained as a data-driven and evidence-based practice that permits further traceability into product fault sources while analyzing bottlenecks and predicting upcoming production resource demands (Lu et al., 2020).

The combination of the physical system and the virtual model in the Digital Twin is an evolution of an existing concept called Virtual Factories, which is a digitalized plant that is integrated with the physical system. However, the Digital Twin has added functions compared to Virtual Factories, it includes real-time synchronization with the physical objects in the system (Negri et al., 2017).

This provides the virtual model to evaluate, validate, and verified the physical system and virtualize the information in a vivid way (Tao & Zhuang, 2017). The virtual simulation could then apply as virtual education programs where employees can interact physically with the asset using an avatar (Rasheed et al., 2020). The 3D visualization of a production facility enriched with real-time data from the asset, which increases the understanding of a real scenario. By using Digital Twin that has the capability of putting analysis outputs into context, better decisions regarding existing systems and future production could be made (Tao & Zhuang, 2017). The decision that is recommended could be among several alternatives since the incoming data is consciously being processed and analyzed with algorithms and integration of several inputs (Uhlenkamp et al., 2019). This gives rise to increased value-adding activities and knowledge management by transforming insight from data into actions (Lu, 2017). When various effects can be considered the Digital Twin can act as virtual commissioning of the system with simulation forecasts, analysis and optimization tools (Negri et al., 2017). Hence the smart analysis of data from an accurate estimation of the condition of the equipment, the Digital Twin enable predictive maintenance (Aivaliotisa et al., 2019; D'Addona, Ullah & Sharif, 2017; Rasheed et al., 2020; Susto, Schirru, Pampuri, McLoone & Beghi, 2015; Vathoopan, Johny, Zoitl & Knoll, 2018). Through predictive maintenance, it is possible to reduce the unnecessary maintenance stops in the operation, thereby increasing the utilization of the equipment (Aivaliotisa et al., 2019; Vathoopan et al., 2018).

The optimal application of Digital Twin is to realize a proactive production with a strategy of predictive management and control methods (Zhuang et al., 2018). The predictive production system can make optimal decisions based on the intelligence and self-awareness of the Digital Twin. To be able to make such decisions, the manufacturing need access to the right information at the right time about the market, customers, workforce, processes and physical objects (Lin et al., 2019). The key factors to enable the Digital Twin to make a prediction is integration and interoperability, which can be actualized with real-time data. The integration is needed between various applications and software and interoperability is necessary to get two or more systems to understand each other and to use the functionality of multiple systems (Lu, 2017). The dynamic and integrated system with advance Digital Twin that has the capability of self-adaption and self-parameterization which makes it possible to detect important patterns and application to handle "what-if"-scenarios (Barricelli, Casiraghi & Fogli, 2019; Rasheed et al., 2020; Uhlenkamp et al., 2019). Risk assessment is then feasible due to the ability to synthesize unexpected scenarios. The manufacturing can then become proactive by using Digital Twin to change and adjusts the physical system through initiating or implementing action automatically (Qi & Tao, 2018; Uhlenkamp et al., 2019; Zhuang et al., 2018). The predictive manufacturing with the use of Digital Twin's feedback mechanism, real-time remote monitoring and control is possible. To allow the use of remote monitoring and control high computing power is essential along with fast communication in the IoT (Rasheed et al., 2020).

3.6. Shop-floor management

In manufacturing products, the shop-floor is an important area where resources are located and organized to create the final product (Tao, Cheng, Qi, Zhang, Zhang & Sui, 2018). The shop-floor works as a convergence point for information flow, material flow, and control flow. It is a common conundrum for companies on how to attain high production efficiency and low production cost while maintaining the product quality in the shop-floor. The companies also need to understand which type of management and control methods that should be used to achieve this. The evolution of shop-floor management and control has gone from single-point management to integrated management, collaborative management, and smart management. Several enterprise information systems, such as Manufacturing Enterprise System (MES), Enterprise Resource planning (ERP), Product Lifecycle Management (PLM), and Product Data Management (PDM) were first developed in the single point management phase. Due to the rapid technological advancements of information and communication technologies e.g. IoT, cloud computing, Big data, and AI, the method for implementing shop-floor management and control must undergo change. With these rapid changes, it is imperative for companies to achieve smart production management and control in their shop-floors (Zhuang et al., 2018). When the shop-floor has transitioned into the interaction between the physical- and virtual space, the lack of available data presents a problem for further development of the shop-floor. As well as faulty resource management, where the production plan does not correspond with the actual production that results in inaccurate process control. Currently, many companies have not achieved electronic data acquisition or predictive management and control, therefore these issues are important for companies to focus on to further develop their shop-floor management (Zhuang et al., 2018). To address this, Digital Twin technology can be an effective approach, it enables real-time interaction and further develop the convergence between the physical- and virtual space (Tao et al., 2018). The different functions and systems required for Digital Twin in the shop-floor will be described in the following paragraphs and are visualized in figure 3.

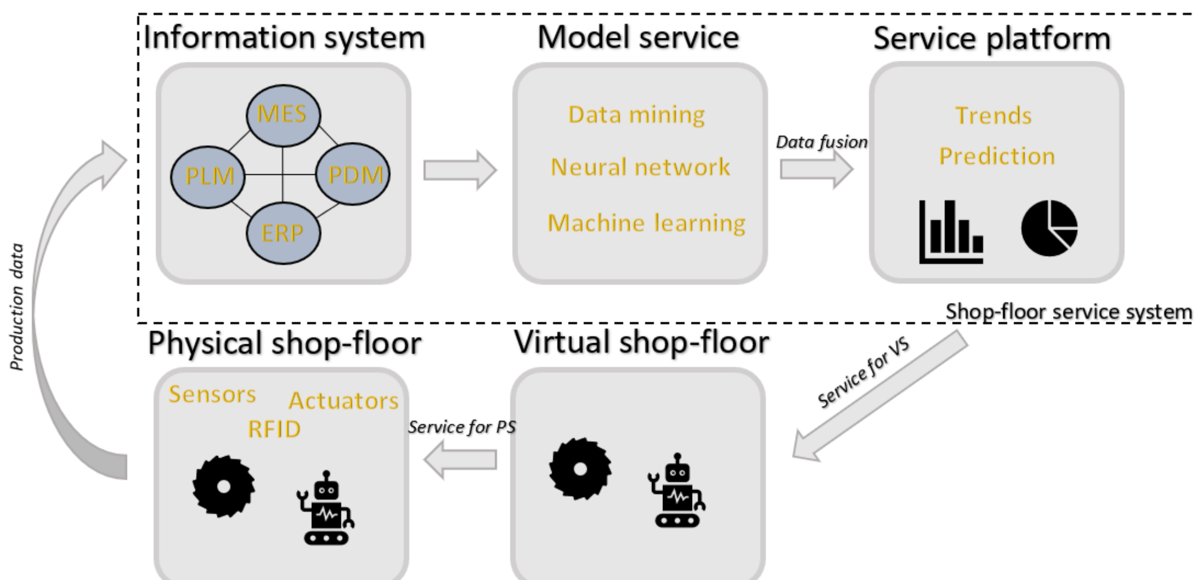

Figure 3 Shop-floor Digital Twin

3.6.1. Shop-floor Digital Twin

The concept of Digital Twin Shop-floor can be used to achieve the physical-virtual convergence on the shop-floor that is imperative to reach smart interconnection and interoperability between the physical- and virtual space. The Digital Twin in shop-floor drives the production through data that is provided from the virtual and physical space and fused data. This makes the virtual and physical space synchronized and optimize the two parts. Fused data is comprised of physical and virtual data that has been through comparison, association, combination, and clustering, which is then integrated and converged into fused data (Tao & Zhang, 2017). Since the Digital Twin contains extensive data from the sensors in the operation and the execution system the virtual part of the Digital Twin is a representation of the environment and process state (Rosen et al., 2015). The physical shop-floor of the Digital Twin consists of physical objects that currently exist on the shop-floor. While the virtual part is the reconstructed digitally mapped version of the physical shop-floor. By creating Digital Twin in the shop-floor the working progress, working status of stations, and manufacturing resources in the physical shop-floor can be mapped realistically and accurately in the virtual space (Zhuang et al., 2018). Some of the information that should be known of the working process in the Digital Twin is the process planning background such as part type and material and the process planning goals, which is dependent on the machining feature. The process planning information e.g., machine, tool, and fixtures should be known as well, this can then be used to evaluate the process knowledge by the Digital Twin (Liu, Zhou, Tian, Liu & Jing, 2019). The virtual and physical parts of the Digital Twin in the shop-floor exchange data/information/knowledge through Big data storage and a management platform that analyzes the incoming data (Zhuang et al., 2018). Since the data becomes integrated, data silos are eliminated, the fused data contributes to making the resulting information comprehensive and consistent (Tao & Zhang, 2017). A benefit of constructing Digital Twin in the shop-floor is the ability to both monitor and track the condition of the physical shop-floor continuously (Zhuang et al., 2018). By using the data from the sensors and execution system in combination with models from the Digital Twin, simulations can be created to aid and anticipate actions of the production system (Rosen et al., 2015). It is also possible to simulate, evaluate, validate, and verify the shop-floor production activities and production processes of the Digital Twin through the virtual part, which results in an optimized production strategy through the simulations (Zhuang et al., 2018).

Since a shop-floor Digital Twin can monitor and track the physical shop-floor operating condition, certain shop-floor activities are enabled e.g. production logistics planning, manufacturing resource allocation and scheduling services (Zhuang et al., 2018). There are several Digital Twin requirements for integration planning. One of the requirements is to have the availability of an up to date bill of resource to know how different resources and assets should be combined. The bill of resources should be comprised of both the planning object identification numbers and where the resources are located in the physical factory in the Digital Twin model at all times. This can reduce the time spent on integration planning. Another requirement for using Digital Twin for integration planning is that the cycle times of the stations, as well as the production line, must be included in the Digital Twin. It is necessary for the Digital Twin to contain the processes of individual cycle times and the idle time of each robot. The Digital Twin should have information regarding the varying distributions and load levels over the joining points of the robots. By utilizing these different information sources, bottlenecks and capacity can be identified by a Digital Twin in the shop-floor for the integration planning. The data over the processes individual cycle times can be analyzed for the purpose of saving money by optimizing the planning of the cycle times (Biesinger Meike, Kraß & Weyrich, 2019). To construct the production plan data is needed as a foundation to make decisions from, one is data regarding equipment capacity (Tao & Zhang, 2017). The production plan is simulated before implementation to examine for faults and eventual modifications are made (Tao & Zhang, 2017; Zhuang et al., 2018).

A vital part of Digital Twin is the necessity of handling data and information exchange (Lu et al., 2020; Rasheed et al., 2020). This is also a significant obstacle in creating a Digital Twin in the present since there is an inability to exchange data and communications between different standards due to data silos. The silos are created through incompatible communication stacks in the layers of the OSI model. To achieve a higher degree of inter-communication companies are adopting Ethernet-based standards (Lu et al., 2020). It is vital to ensure that the data exchange transpires without delay, which can be a challenge with the large data volume and generation rate, as well as the significant variety of data (Rasheed et al., 2020). To reduce communication gaps between different stages in the product lifecycle and gaining a more autonomous process planning, it is important that the exchange of product data between systems is facilitated. It is essential that Product Manufacturing Information (PMI) such as 3D model data and geometric tolerances is represented in the Digital Twin to provide a technical base. ISO 13399 is a standard that utilizes a neutral "language" to describe products in digital formats. This enables the Digital Twin to perform CAD/CAM/CNC integration, tool management, product data management and manufacturing resource planning. The ISO standard focuses on the exchange of industrial product data regarding cutting tools as well as tool holders (Lu et al., 2020).

3.6.2. Shop-floor service system

The service system provides services to support the management and control the operations in the production system and provides to support evaluation of the virtual system (Leng, Yan, Liu, Zhang, Zhao, Wei, Zhang Yu & Chen., 2019). The resources to the service system come from the information systems, model system, and visualization approaches (Tao & Zhuang, 2017). The Digital Twin contains the exchanged data and gets stored in a single data source that utilizes support for the physical system, virtual system, and the service platform (Zhuang et al., 2018).

3.6.3. Information system

Digital Twin used in shop-floor needs data from multiple information systems to support the service platform in the Digital Twin. The enterprise information systems are often MES, ERP, PDM, and PLM (Zhuang et al., 2018). The service system can also include support systems such as Customer Relationship Management (CRM) and Supply Chain Management (SCM) (Tao & Zhang, 2017). The information systems combine synchronous technology for real-time data of equipment monitoring, virtual simulation, and MES (Leng et al., 2019). ERP provides the shop-floor system service with information about delivery, quantity, cost, and quality. The ERP can then define the predefined process to the enterprise resource planning, where necessary resources such as human workload, machines, products, and equipment can be allocated (Tao & Zhang, 2017). Other useful data for the service system are data from the production system, where MES functions as an information exchange between the production system and the ERP. The system enables the collection of data from the shop floor to the Digital Twin regarding material input, consumable usage, and production flow. This information is vital for the Digital Twin in the shop-floor to control the process and recognize trends for production efficiency (Coronado, Lynn, Louhichi, Parto, Wescoat & Kurfess, 2018). However, many manufacturing companies experience difficulties in using MES, which causes a reduction of work efficiency (Jeon, Um, Yoon & Suk-Hwan, 2017). Some of the issues are manual data entered by operators, limited real-time capability, and issues with interoperability and data sharing between elements (Coronado, Lynn, Louhichi, Parto, Wescoat & Kurfess, 2018). To support the utilization of Digital Twin and situations in real-time, smart MES is a necessity where the infrastructure and architecture support data collection, analysis, integration of manufacturing data and cooperation with the different elements in the system. The data integration and transformation must permit different types of system to collaborate, therefore unified data models must exist to accommodate the enterprise information system and the shop-floor data. Additionally, the smart MES needs to include a platform with Big data module and synchronized functionality modules, to analyse and visualize the large amount of data that have been collected (Jeon et al., 2017).

3.6.4. Model service

Digital Twin in the shop-floor works as a driver for the virtual and the physical system. The virtual model of the shop floor contains information regarding geometry, physical, behavior, and rules (Tao & Zhang, 2017; Zhuang et al., 2018). The virtual model gets its data from geometry from 3D models that describe shapes, sizes, position, and assembly relations of machine components. To analyze the physical state, information to the virtual model is collected from e.g. capacity, force, torque, stress, resistance, and temperature (Tao & Zhang, 2017). It also provides information about the physical systems production line model, manufacturing resource models, personnel models, and material models (Zhuang et al., 2018). The behavior comes from a description of how the machine responds to mechanisms under driving factors and is collected through the NC program (Tao & Zhang, 2017).

The amount of data that the Digital Twin processes are collected from different sources and classified as Big data. There are several factors that need to be considered when implementing Big Data analysis solutions for Digital Twin industrial applications. The factors are e.g. hidden meanings between features and how they relate to other features, processing real-time data without delay and ensuring high-quality data with low noise and data conflicts (Lu et al., 2020). The collected data need to be of high enough quality, it is not useful to have a large amount of low-quality data (Rasheed et al., 2020). To achieve high-quality data, it is important to clean the incoming raw data and transform it into ordered, meaningful and simplified forms without the noise and missing data (Lu et al., 2020; Qi & Tao, 2019; Tao & Zhang, 2017).

It is essential to remove both conflicting and redundant data records since noise can lead to misleading results in the data analysis (Lu et al., 2020). After the data cleaning, data mining is performed to support the creation of models and further analysis to detect patterns and trends. This by adding rules of association, constraints, and deduction to the collected data for the Digital Twin. The mined data is then used in data fusion to integrate data from different sources and to gain a more consistent and extensive interpretation (Tao & Zhang, 2017). To fill the missing data and reduce the noise to improve the quality there is a method called Generative Adversarial Networks (GANs). The method works through two networks called generators and discriminators, these are trained through Machine Learning to outperform each other. This has the result of generators that can create data that is indistinguishable from data created in the physical space (Rasheed et al., 2020).

With the fused data based on the modelled data and operation data, the Digital Twin can then evaluate, validate, and verify the shop-floors accuracy. This enables the identification of trends and predictions in the service platform and could be visualized in the Digital Twin to provide feedback to the service system on potential changes that need to be done (Zhuang et al., 2018). The optimized result from the fused data in the Digital Twin system, production strategy can be improved and transmitted to the Programmable Logic Controller (PLC) in the physical system (Leng et al., 2019). Due to the application in the model system e.g. machine learning, neural network, and data mining, the transmitted prediction result can result in autonomously decisions with self-adaptive and self-reconfiguration functions. Hence achieve the ultimate goal of proactive production management and control (Zhuang et al., 2018)

3.6.5. Physical shop-floor

A production system with objects connected to RFID, Auto-Id and embedded sensors becomes smart objects with real-time data that enables identification and tracking through the whole production process and thereby can detect real-time changes in the environment (Guo, Zhong, Lin, Lyu, Rong & Huang., 2020; Leng, et al., 2019; Tao & Zhang, 2017). Fieldbus and industrial Ethernet are usually employed to connect the smart objects, actuators, and controllers with the shop-floor. With the connected shop-floor it is possible for real-time communication, protocol standardization, and integration. The physical system then provides real-time status that can be transmitted to the shop-floor service system (Tao & Zhang, 2017). The applied RFID and sensors can provide collected data regarding equipment status and operation, personnel status data, and production logistical data (Zhuang et al., 2018). Due to the different interfaces and communications protocols that are used to transmit sensor and RFID data complicates the implementation possibilities of infield data access to virtual space (Tao & Zhang, 2017). To transform the data into a uniformed interface and protocol, open-source- and read-only standards based on eXtensible Markup Language (XML) can be used to permit communication from machine to machine and machine to operator. MTConnect is an example of a standard that uses neutral language to shield the heterogeneity of protocols and interfaces and makes it possible to collect data from machine tools (Coronado et al., 2018; Tao & Zhang, 2017). The smart object can then be shared and managed in digital space (Coronado et al., 2018; Guo et al., 2020). The smart object creates signals so that the Digital Twin can capture operation data from the physical process. The information such as objects ID, attribute, and current status can be transformed into digital messengers using encoders and then transmitted to the Digital Twin which then are synchronized with real-time manufacturing status. Product information together with process data using MES provides the physical system with valuable information to the virtual system that makes the information visual and traceable (Guo et al., 2020).

4. EMPERICAL FINDINGS

This chapter will cover two sections of the empirical findings from interviews that were conducted at the case companies. The purpose of the first section was to interpret challenges in the current state and future ambitions regarding the critical success factors transitioning to smart manufacturing; organizational, operational and technological. The second section is intended to gain a deeper understanding of how shop-floor management is designed and the current state of the physical shop-floor at the case company, to yield insight on what changes are needed when implementing Digital Twin.

4.1. Current and future state of the case companies

The case study included a collaboration with three global manufacturing companies located in Mälardalen, Sweden. The case companies have in common that machining is a significant part of their shop-floor processes. Argon, Gallium, and Vanadium are the given individual pseudonyms to keep the case companies anonymous. The case companies are involved in an external project together with MITC, with a focus on simulation and Digital Twin. The lack of knowledge of what defines Digital Twin and its functions is a mutual issue for the case companies. However, the companies have the ambition to increase the utilization of digital solutions.

Several interviews were conducted with the aim of obtaining a thorough understanding of the case companies' situation and how the application of digital technologies can contribute to increase business value. Hence, the interviews were performed to grasp the current state and future ambition for the case companies by exploring the critical success factors to achieve smart manufacturing.

4.1.1. Current organizational state

Argon does not have a companywide approach in what changes towards Industry 4.0 should be realized. However, the company state that preparation for their employees before the change in manufacturing is important. Shortly, employees need to change their mindset and be educated on how to work with new challenges, e.g. handling-, storage and utilize data. Argon explains that it is common practice to involve the employees that will be affected by the change of projects that are running. Although, the company is uncertain about how to involve the operators or other personnel efficiently in the changes that will be made. Gallium is very prone to changes and also presses the importance of involving the operators from the start of projects. This is done mostly in an effort to alleviate the resistance to change in the implementation phase, but also because of the knowledge that the operators possess. Vanadium acknowledges that it is the people that create value not the systems and press the importance of having a culture at the company that is ready for change. Similar to Gallium, Vanadium involves the operators in change work and much of the projects originate from frustrations from operators and quality managers. The resistance to change is addressed at Argon as well through involving the employees early in the change process. At Gallium the operators are the ones that are the most knowledgeable of their work area and are very involved in deciding how the work tasks should be performed. The company also offers continuous training and schooling to further competences, often through internal courses. The importance of continuous training has also been stressed by Argon and the need of prioritizing competence development. Vanadium also offers internal courses but have additional opportunity to send their employees to take courses at universities in order to further the competence of their personnel. However, Vanadium mentions that the available courses for the employees are not fully utilized.

4.1.2. Current operational state

Argon is currently focused on innovation and developing new products at a higher pace and being cost-effective, this translates into focusing on the production flow and where to produce which product and at prime production cost. One of the biggest challenges in achieving the company's goals is having a continuously high quality while keeping the cost down to attract customers. The challenge is expressed by all the case companies, for Vanadium and Argon it is mainly due to the lack of real-time data that hinders an efficient quality control. It also restricts the capability to make sure everything is running accordingly and to ensure the availability of the machines. Another issue to obtain high quality is the difficulties to determine the root-cause, which led to symptoms being treated but the problems keep occurring. However, Gallium has high demands on the traceability, if quality problems arise after the product has left the factory, the company must be able to quickly answer how the unit was assembled, by who and at what dimensions. Although, the traceability is limited to batch-level instead of individual parts, which implicate that it is not possible to identify which specific machine produced the unit. To have traceability on a batch level is mutual for the case companies and can lead to difficulties to find causes for problems on individual parts. At the case companies manufacturing, the components are measured for deviations outside the tolerances' threshold from the measurement specifications, to avoid delivering components with quality problems. They measure according to frequencies or at pre-planned checkpoints to ensure that the components are within the tolerances. Vanadium has a system that handles the quality reporting where the operator has entered the deviation and the quality manager rectify the deviation and provides feedback to the manufacturing. Since the quality control at the case companies is done by examining measure for deviation outside the tolerances' threshold and therefore there is no information on what is happening within the tolerance and has been expressed as a future ambition for Gallium to gain such knowledge to better understand the processes.

Quality problems at the manufacturing processes are a mutual issue for the case companies and causes unplanned stops. When the unplanned stops occur, corrective maintenance must be done which decrease the stability of the process. Vanadium manually logs when the unplanned stop occurs and the possible cause of it, however, the problem reappears since it is difficult to find the root-cause. The company believes that the problem has to do with the aging machine park, as well as the limitation for tracking historical data to detect trends. To circumvent this problem, Vanadium wishes to have more digital imprints to maintain high performance on machines, thus avoid unplanned stops. In Argon case, either a third party for maintenance is used or a maintenance department within the company. The department gets the information from a system where the maintenance tasks have been manually entered by the operator. The planned maintenance is often done on experience and in many cases it is not based on facts, this can result in maintenance being either done too often or not enough. At Gallium unplanned stops are common since their machines are constantly running. The machines are utilized roughly 70 percent of the total time, with the planned stops already deducted. Both Gallium and Vanadium have a system to follow up if an unplanned stop occurs, Gallium:s system checks if a machine is running and logs stop and start times. Argon has PLC interface that is specified to machine suppliers to permit deriving and follow up the signals from the machines. However, this has not generated a substantial effect at Argon since the resources to handle and analyse the data is lacking.

4.1.3. Current technological state

All the case companies have experience in working with automation, some more than others but all the companies have seen benefits of implementing automation in their factories. Gallium has an extensive history with the use of automation and has been established as a strategy to stay competitive. The case companies use automation to increase capacity and quality, ergonomic, safety, work environment reasons and to reduce unstimulating work tasks for the operators.

The collection and type of data vary between the case companies. A mutual issue is difficulties in collecting real-time data, though Gallium can collect a limited amount of real-time data. The case companies have a limited amount of sensors in their production, hence the data collection does not cover machine performance and behaviors. Instead, the data is comprised of measurements of components, timestamps and machine dimensions. The case companies have in common the realization and necessity to take care of the data that is being collected and make it available and visual for the employees. Argon has a gap between their ERP system and the machines, which hindrance the ability of the employees to take care of the data that is collected. Another factor that is similar in the case companies is an aging machine-park, the machines are old and were not made to be able to collect data from. Gallium has rewritten their technical specification to require that new investments of machines must be able to collect production data. One challenge the case companies have in using the data that is collected is being able to search and navigate in it. The employees are successfully able to search for information in one system but due to data silos, it is difficult to accomplish wider searches across multiple systems. Another obstacle for Gallium in searches across systems is that different systems use different name-standards for the same components.

A mutual issue for the case companies is that the digitalization effort has not been successful yet since there still exists a high documentation rate with extensive paperwork within the factories. Argon has tried to examine in their product groups what could benefit them from Industry 4.0 and digitalization. They are in the process of a pilot study to determine a requirement specification for MES, something that Argon hopes to build an IT-structure from. Gallium already has an MES system implemented in their factory and is used in combination with a visual shop floor program. The program is connected to a machine follow-up system and can thereby visualize the data.

4.1.4. Future organizational ambition

The case companies realize the need to invest resources to achieve a smart factory. Argon has many ideas on what needs to be done in the future to approach smart manufacturing and Industry 4.0. To realize those ideas, the company has teams where their tasks are to run projects to stay ahead regarding technology development. Argon is not alone with having teams that work with digitalization and improvement towards a smart factory. Vanadium and Gallium have teams where the work tasks are to be prepared for the future. That means among other things to invest in new technology and new products to stay competitive on the market. Because Gallium is well-versed in automation the goal is to explore digitalization opportunities. While Vanadium and Argon aspire to explore automation in combination with digitalization in the future. Argon acknowledges to reach that goal, new qualifications will be necessary for the future. Automation engineering and activities that are associated with industry 4.0 will be essential to support the development and implantation of new technologies.

Gallium has digitalization-roadmap on a local and a global level, whose purpose is to help the company to plan what activities should be done, both long and short term. Argon is in the beginning stages of developing a local strategic digitalization and Industry 4.0 roadmap. The purpose of the roadmap is to find activities that will be beneficial and cost-effective in the future for the factory. While Vanadium only has it on a global level, where activities that support the goal within the next three years towards a digital factory are explicitly definite. The lack of a local roadmap eventuates in difficulties for the factory in identifying where opportunities for digital development is suitable and the purpose of the transforming. Mutually for the case companies is that the development of digitalization for the future, first needs to start by investigating internally how the factory support digitalization with factors such as IT structure, data management and standardization. An additional factor why it is important to perform a thorough evaluation of suitable areas is according to the case companies, the high investment cost of new technology and digitalization.

In the future, close relationships with the customers will be necessary, with high service and extended industrial value chain. Argon emphasizes to gain such a relationship, a new business model with customers and supplier must be developed. The future business model must be cost-efficient with a service agreement for after-market. For Gallium the challenge is that each order is unique and personalized which leads to difficulties for standardization and flexibility. The case companies also anticipate that factories in the future will involve smarter machines that can communicate and perform conditional monitoring that will help the organization to make better decisions that is based on real-time data. This will change the evolvement from people in manufacturing but according to the case companies, it is a long way before machines can replace humans.

4.1.5. Future operational ambition

Argon believes that the process can be optimized in the future with digital IT-structures with better synchronization between the companies and suppliers' interfaces. Currently, Argon operation procedures are strict and standardized, which the company sees as a limitation for the flexibility in the future. While Gallium sees the lack of standardization due to the need for personalization as a challenge to get the process more flexible. Both Argon and Gallium acknowledge that the operations are required to be more flexible to take advantages of future opportunities. To implement new technologies, the companies emphasize that the starting point is to look at what machine is most suited, e.g. ability to get real-time data and proper control systems. The future processes will then be able to have several measurement points with real-time data. Real-time status will be provided for the process and possibility to change the input data in the system, hence be able to detect deviation during the process. This will according to the case companies lead to better control over the whole process and minimize quality errors detected at the end of the process. Gallium's vision is that future processes will make the data more available and visual for the user. The main goal for all the companies is to have Machine Learning that recognizes and verifies deviation so that conclusions could be drawn based on stored and filtered data. With Machine Learning, the relationships between stations and machines will also take into consideration even within the tolerance threshold according to Gallium. Argon also has ideas in the future to start use-cases with the goal of condition-based maintenance, the purpose of this is to reduce downtime for the machine and to be able to perform maintenance without interrupting the process. With condition-based maintenance, Argon believes that waste will be reduced since the operation will occur based on facts and not assumptions.

4.1.6. Future technological ambition

All the case companies acknowledge that digitalization is an important feature to stay competitive in the future. They realize that the manufacturer needs to be more connected and have efficient ways to visualise and manage data. They believe digitalization will make the company more efficient and utilize decision making. For the case companies, the digitalization should not just be implemented for the sake of it, it needs to be carefully investigated where it can create value. Technologies such as real-time monitoring and automated guided vehicle were implemented at Vanadium a decade ago but were removed since it did not create any value and the maturity level of the organization was not synchronised with the technology. With Industry 4.0 a new attention has been directed on such technologies and has led to a new investigation for Vanadium in were to implement real-time monitoring to create value. They believe that the maturity level is now more intact and to use a new approach of starting smaller and let it develop over time. It is a mutual goal for the case companies to implement new advanced technology such as Digital Twin. However, they are uncertain what is covered as Digital Twin and how to define it. Some of the case companies regard it as a simulation, while other consider that the Digital Twin needs to include more features.

The case companies need to have high connectivity and digitalization on both product and process level to utilize advanced digital technology. Argon believes that implementing new advance digital technology will increase their technical availability, capability and overall equipment effectiveness. However, in Argon’s case a better IT-structure connecting ERP and MES systems that can communicate the data need to be constructed before implementation. Gallium has a functioning system that can collect real-time data, the vision for them is to utilize the composed data and with Machine Learning take advantage of it. Since Vanadium does not currently collect real-time data the maturity level of connectivity and digitalization is limited but the company sees the benefits and strives to become more digital. For Argon, the high connectivity and digitalization will lead to an opportunity in the future to expand their business model by having control over the products across the world. This facilitates services to continue at the aftermarket to support the customers. The global control over their products enables the company to provide suggestions to the customers e.g. when service is needed or when they need to change a component. The digitalization will thereby in the future not only be useful internal at process level but also externally on the product level.

The case companies’ ambition with digitalization, is that it will help them in the future to become more proactive instead of reactive, thus have better availability on the machines and better control over the equipment regarding quality and potential issues. To obtain that state, the case companies stress that the data is required to be more digitalised with accuracy. For the case companies, the development of digitalization in the future is also interesting for the sake of utilizing simulation and emulation. The optimal state is to test a production system on a computer based on facts to minimize installation time, production loss and issues cause by humans. It is expected that the digital solution can take several machines and automation solutions into account.

The challenges for the case companies vary based on how far along each are with data management and real-time monitoring, but a common obstacle consists of an aging machine park that is not equipped to be adapted to new technologies. The solutions to integrate such equipment are difficult according to the case companies and to transition towards Industry 4.0 for a company that has been running for a long time is challenging. It is not only a formidable task to integrate the older machines, but it is also a big challenge to get a unified system for digitalization. In the future Argon sees a change in how companies will invest in equipment, for example, the company will no longer just want to buy the hardware, they will also want to have a digital representation of the equipment.

4.2. Assessing shop-floor management and physical shop-floor

The investigation of the critical success factors gave rise to the ability to capture the challenges and opportunities in the case companies. It requires a deeper insight into a process to know how to address the challenges and opportunities. Therefore, this section will cover how shop-floor and supporting functions is designed for a production cell to understand how the implementation of Digital Twin in the shop-floor will change the current state and how it can be applied to achieve increased business value. To gain such knowledge, an investigation based on interviews of Argon’s manufacturing process of metal components was conducted. The process includes two cleaning steps and four machining processes; washing machine, manual polishing, cutting, turning, welding, and laser cutting. The interviews were focused on shop-floor management, the physical shop-floor, and shop-floor service system, which was identified in the literature review as important areas to consider when implementing Digital Twin. Shop-floor management is important to consider for understanding how the management structure is designed to support the production process and how decisions and resource allegation is executed. The physical shop-floor was examined to identify technologies, input- and output data as well as how the data is managed to comprehend the current state and eventual challenges. To understand the connection between shop-floor management and the physical shop-floor, the shop-floor service system was examined to grasp how communication and sharing are performed of the information. Based on the interview and documentation, a process map of Argon's current shop-floor was conducted, see figure 4, and will be described in the following section.

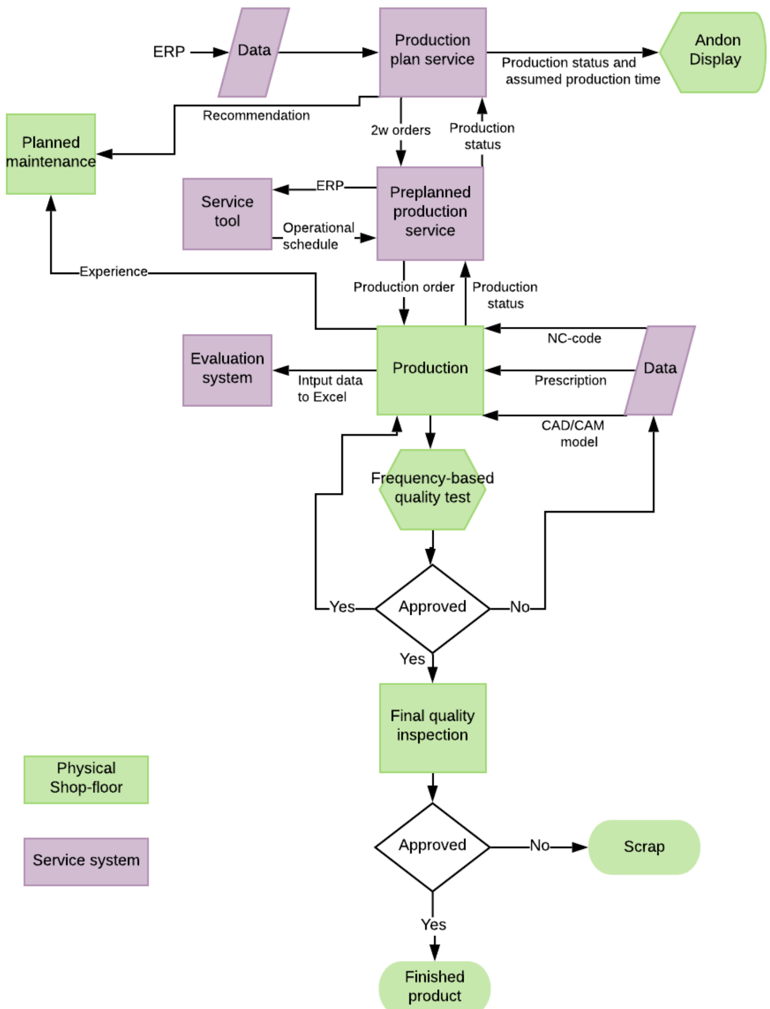

Figure 4 Process map of Argon's current shop-floor

4.2.1. Shop-floor management

The production planning department at Argon receives customer orders that consist of a specification and is broken down into bill of materials. Argon is able to plan the production orders with the information in bill of material, the status of material stock and the production status from the physical shop-floor. The production planning department plans the customer orders into two weeks intervals which are then notified to the production leaders of the preplanned production service in the factory through paper forms and weekly meetings. At the meetings, the current production order’s status is reported, and the new ones are discussed. The status of the current production orders is important for the planning department since it is necessary to consider eventual machine problems and if personnel are on sick leave when the production planning is done to prevent delays in deliveries to the customers. Production plan service also gets important information gained from the data of the Andon system that is displayed in their production. The Andon display shows the number of minutes that the machines have been active and visualizes the time it should take to produce the production order. The data that is transmitted to the Andon display is provided by the service system. The transmitted data is comprised of assumed production time and actual production status from the ERP system. If the assumed production time does not correspond with the real-time spent, the pricing of the articles might need to be adjusted since the price is mostly based on the expected time to produce the product. The comparison with assumed and real-time spent for the production order is also beneficial to increase the accuracy of the production planning. However, it is difficult and time-consuming for Argon to estimate the cycle time and how many articles have been produced since their production is shown as the time spent producing articles instead of number of finished articles. The exchange of data regarding the production plan service is visualized in the upper part of figure 4.

The optimization of the production is performed manually in the preplanned production service by the production leader or a team leader. The optimization is performed by deciding how the orders are going to be executed e.g. the sequence, which machines and the timeline. This is mostly done with the help of Excel to both plan and visualizes the result, which is an effort to facilitate the understanding of the sequence that the articles are going to be manufactured. This transmission occurs in the service tool and the resulting production sequence is then executed in the production, as shown in figure 4. Although, a significant obstacle with performing the manual production plan for order execution in the service tool is the difficulties to optimize the sequence when a component requires several operations and the machines that produce the component are shared resources for other components as well. This can be solved in the future by using a more advanced evaluation system for planning which sequence the articles in the production order should be manufactured to achieve an optimized flow with shorter lead times. At the moment, the optimization of the production flow is done by minimizing the changeover times through manufacturing the same articles that are found in the different production orders at the same time.

As shown in figure 4, Argon has planned maintenance in their factories based on recommendations from equipment suppliers and from operators' experience. According to the case company, this can lead to waste of resources and time by performing the maintenance more often than is necessary to ascertain that failures do not happen. However, one benefit is being able to account for the downtime of the machines and cells in planned maintenance for the production planning of customer orders. Although, Argon considers conditional maintenance as an optimal state.

4.2.2. Physical shop-floor

Currently, real-time data from the production cell is not analyzed at Argon. One of the reasons is that the functions of the sensors at the shop-floor are limited to position measurement connected to the automation solution that does not generate any useful output data. The output data that is generated is captured in the PLC. It is possible to extract that data, but Argon does not have an appropriate system to manage the data. However, it can be manually entered into an Excel-file but there are not enough resources to perform data analysis with that approach. This is presented in figure 4 by having an input arrow to the evaluation system and no output arrow to visualise that the data is not utilized. Although, the case company wants to collect real-time data and to be able to make use of the output data. When it is possible to collect such data the case company believes it will be beneficial, especially to obtain information on Overall Equipment Effectiveness (OEE) to improve efficiency at the shop-floor.

The biggest challenge at the cell on the shop-floor is the stability and to achieve an even production flow without disruptions. The problem is not connected to a specific machine instead it is a continuous challenge through the entire process. The reason for an unstable process is usually due to the different operators involved in the process steps. The disruption to the processes arises when the data is manually entered, hence mistakes could be made that have consequences for the entire process. Problems can also occur when operators do not use the same standardization as it creates instability. At Argon, there are no significant quality problems except that the welding process leaves residual material on the products. This is an important issue since the customers have a high requirement of purity and the residual material may interfere with the end-product at the customers' side.

Argon has different goals for the shop-floor and one of them is to have a virtual commissioning for the cell to facilitate installation and testing. The purpose is to reduce disruption at the shop-floor by optimizing the process through first trying and doing eventual adjustment at a digital platform before implementing the changes at the physical production system. When all the equipment and devices are connected to the digital platform emulation is then possible and could be beneficial for improving the production and being used for education.

4.2.3. Shop-floor service system

There are different variants to run the production cell at Argon. To know which flow the operation will take for a specific order, the article number is manually entered in the Human-Machine Interface (HMI). Additional input data received by the machines is the NC-code that describes the path the machining is supposed to perform. To set the machine to specific orders, the parameters such as current and pressure must be manually entered by the operators. This procedure only needs to be done once since each article number has an individual prescription that will be stored in the machine. The manually entered data in the shop-floor has been identified as a fault source since mistakes occur due to human error. This is one of the reasons for the goal of increased digitalization and becoming a paperless factory. Argon recognizes that one way to decrease paper and manual handling is by enabling the production orders with all the product specification to go straight into HMI. The data that is already digitalized is the description of how the machining space in the equipment is constructed for the five-axis machines. The CAD models are used in the CAM module to generate the path for the machine tools to check that nothing collides. As shown in figure 4, the previously mentioned NC-code, prescription and CAD/CAM are the necessary input data for the machines in the production.

Argon's service system is mainly an ERP system that utilizes incoming data from orders to plan and optimize the shop-floor. Information such as article number, order number, batch sizes, and process flow are manually entered in the ERP system. However, the case company aims to digitalize the factory and become more proactive instead of reactive, hence the ERP system is not enough to realize those goals, and one important step towards digitalization is to implement an MES. Several factors have been the driving force for using an MES, one of them is that ERP is insufficient to manage real-time monitoring and control. According to the case company, the system is not enough to handle activities that require quick feedback. If an ERP system would be used to monitor and control the machines, the slow response from the system would lead to equipment standing still and waiting for the processed data to give a directive. The result would be decreased productivity and efficiency on the shop-floor. Another reason for using an MES for Argon is to have a suitable system that could handle signal exchange to collect, store, and filter production data.

Argon wants a system that tracks and identifies quality deviations with the help of AI algorithms or vision techniques, that can then be used to create statistics over quality connected to article number or the production prescriptions of the articles. They also want the system to be able to alert when defects are detected without disrupting the process. According to the case company, if an MES is implemented, they can more easily find the root-cause with data from the MES instead of treating the symptoms as it is done today. To check for quality deviation and evaluate the quality of the manufactured components, frequency-based quality tests are performed as well as the first piece check at every changeover. The rate of the frequency varies between different types of processes, some have a higher rate, while other processes have a lower rate of quality testing. After a changeover, the first component is always examined to ensure that it is within the tolerances and that the machine parameters are properly set. As shown in figure 4, if the component passes the quality check the operation can start. If the component is not approved the input data to the machine need to be adjusted until the quality check is passed. The last station of the production process consists of manually polishing the produced components to remove residual material and a final quality check is performed. Since it is the last station, the component that does not pass the final quality inspection becomes scrap. Argon also performs frequency controlled destructive tests at the welding station, something that they see a possibility to replace with temperature sensors or an advanced x-ray machine and thereby reduce waste. The data that is generated by those solutions could then be used to identify patterns and trends.

5. ANALYSIS

This chapter is structured based on the two research questions. To be able to answer the first research question on the benefit of Digital Twin for increased business value, the critical success factors need to be evaluated in relation to case companies' challenges and ambition towards implementing Digital Twin. By performing a comprehensive analysis of a shop-floor manufacturing process and the support functions, the second research question on what requirements in the shop-floor is necessary to implement Digital Twin can be analyzed.

5.1. Critical success factors to consider before implementing Digital Twin

According to Tao, Qi et al. (2019), the Digital Twin is closer akin to the engineering category and industrial practice. With the lack of a unified definition of Digital Twin (Uhlenkamp et al., 2019) a connection could be made to the close relationship of Digital Twin to the industry (Kritzinger et al., 2018). However, it is problematic to comprehend what previous research means in their definitions of Digital Twin regarding the type of data and how the data is transmitted between the physical and virtual model of Digital Twin. The authors of this thesis interpret that Digital Model is considered as a Digital twin according to Gabor et al. (2016) and Guo et al (2019). This interpretation is based on that the authors' definitions do not describe how the data needs to be transmitted, whereby the Digital Model that transmit manual data between the two spaces is counted as Digital Twin. While Glaessgen and Stargel (2012), Grieves (2014), Rasheed et al. (2020) and Zhuang et al. (2018) emphasize that real-time data needs to be transmitted in digital twin, though, it is not expressed if the real-time data needs to be two-way interaction. This indicates that real-time data from the physical to the virtual space is a significant feature but allows for interpretation of how the data is transmitted back to the physical space. Thus, the Digital Shadow would be considered as a Digital Twin with open-loop real-time interaction. On the contrary, Tao, Sui et al. (2019), Qi and Tao (2018) and Zheng et al. (2019), stress that Digital twin requires a closed-loop interaction between the physical and virtual model with real-time data, thereby changes in the physical object will affect the virtual model and vice versa.

Uncertainty on the definition of Digital Twin could also be identified within the case companies since the companies view on Digital Twin varies. A connection could be made to the diversity of the manufacturing industry and thus according to Kritzinger et al. (2018), the need for Digital Twin may differ which makes it difficult to have a uniform definition. Since there are a variety of ways to use Digital Twin it could be problematic to know potential implementation areas in the manufacturing. By dividing the concept into different intelligence levels, the Digital Twin's landscape and different dimensions will be easier to grasp. According to the authors, the division can result in that the implementation possibilities of the Digital Twin will become less diffuse since the large scope of Digital Twin will be approachable in smaller stages. This facilitates and clarifies where it can be implemented and what is required to take the next step towards a more complex Digital Twin. Kritzinger et al. (2018) and Uhlenkamp et al. (2019) describe that the different intelligence level depends on the level of data integration between the physical object and virtual model and the complexity of the virtual model.

It is vital for manufacturing companies to adapt the current manufacturing to new digital technology since the development of advanced digital technologies has changed the condition for traditional manufacturing (Lin et al., 2019; Lu, 2017; Negri et al., 2017; Zhuang et al., 2018). However, to adjust the current manufacturing towards smart manufacturing with the use of advance digital technology have been noticed as a challenge for the case companies. Therefore, it is important to determine which success factors are important to consider and what makes a successful implementation of digital technologies. According to Nwaiwu et al. (2020), the critical success factors that need to be aligned with the implementation of the Industry 4.0 concept are organizational, operational, and technical particularities. A compilation of the analysis of combining empirical findings from current challenges and future ambition with theoretical findings regarding utilization opportunities with Digital Twin in manufacturing companies will be presented in tables 7, 8 and 9.

5.1.1. Organizational factors

The rapid development of new advanced digital technology has changed the condition for traditional manufacturing industries (Lu, 2017; Negri et al., 2017). The industries have evolved into smart manufacturing due to the new advanced data-acquisition systems, information- and network technologies (Tao, Qi et al., 2019). A mutual vision for the case companies is to approach smart manufacturing to stay competitive in their markets, which corroborate with Tao, Sui et al. (2019) statement that manufacturing industries aim to achieve smart manufacturing. The empirical findings of this thesis and discoveries from Benvenuto and Bäcklin (2019) indicate that manufacturing companies in Sweden have a low maturity level towards Industry 4.0 and therefore low readiness for implementation of Digital Twin. This analysis can be made since reaching Industry 4.0 indicates that a smart factory is achieved (Li et al., 2017) thus, intelligent manufacturing with CPS (Zhuang et al., 2018). Hence, low readiness for CPS also signifies a low readiness for Digital Twin since the two concepts have similar requirements of a fusion of the physical and virtual world.

To achieve smart manufacturing, companies need to increase collaboration between machines and humans. This results in a connected information network with an increased amount of data that needs to be managed (Chen, 2017). The organization strategy needs to be aligned with business processes while encouraging employees resource availability and readiness (Nwaiwu et al., 2020). It will require the employees to adapt their mindset and change their work tasks (Chen, 2017). Argon corroborates with the policy of involving their employees in change management since changes often affect operators. Although Argon is uncertain about how to involve the operators efficiently, they realize it is important to prepare and educate the personnel. The importance of involving employees in changes is expressed by all of the case companies. The involvement originates from the ambition to reduce resistance to change amongst the employees. Gallium also states that the operators are the ones with the most knowledge of their processes hence it is essential to make use of that knowledge. To further develop their competence, Vanadium and Gallium offer continuously training through internal courses and at local universities. However, Vanadium mentions that the courses are not used to a high degree. With the use of Digital Twin as a strategy over how humans and machine should collaborate could be established by linking the skills and demands that the employees' and the technical system is under (Graessler & Poehler 2018; Lu et al., 2020; Wagner et al., 2019). Digital Twin can also be utilized as a virtual training tool that leads to a higher understanding of how to optimize resources and operational efficiency (Negri et al., 2017). The authors see this as an opportunity to increase the utilization rate of the courses by adding an alternative that is of a practical nature. This provides a visual alternative that can be linked to the theoretical courses. It also provides the opportunity to increase the number of courses based on the company's assets. The employees can gain a better understanding of the equipment and the components behavior since through the virtual model with real-time data from the physical object together with the use of an avatar, the employees can interact with virtual representation of the physical object. With the ability to predict conditions for the manufacturing assets the increased knowledge of real scenarios can be used to prevent unplanned stops (Rasheed et al., 2020; Tao and Zhuang, 2017). According to Zheng et al. (2019), prediction on how the manufacturing assets will behave can result in choosing accurate specifications and requirements for the components. This could be beneficial for the case companies towards achieving increased stability in their manufacturing processes due to the higher consistency of the production through the ability to predict the manufacturing assets. Companies can also use a simpler version of Digital Twin for the purpose of using it as a training and project tool. The virtual model of the Digital twin can be used as a test solution through simulating scenarios before implementation. The operators then have the opportunity to provide feedback on eventual changes and thereby the knowledge of the operator can be utilized to a greater extent, something that has been expressed as a goal by all case companies.

High pressure from a more complex, highly demanded, and knowledge-intensive manufacturing domain has led to the requirement to increase the overall level of industrialization, automation, and digitalization (Lu, 2017). The case companies realize they need to be at the forefront of technology development and have teams with a focus on Industry 4.0. According to Gallium, the pressure of the market domain requirements of a shorter time to market has led to a survival strategy based on automation. By having solid experience of automation, the company is well-versed in the area and instead sees a necessity to expand their knowledge and use of digitalization. Vanadium and Argon do not have long time experience with automation hence have a need for developing further use of automation and digitalization to stay competitive. To reach the goal of a higher level of automation and digitalization, De Carolis al. (2017) and Nwaiwu et al. (2020) emphasize the importance to develop a vision and a roadmap for the future state. This is no exception for the case companies, they all realize that a roadmap is essential to plan where the company wants to be and what activities should be done. Nwaiwu et al. (2020) confirm that a roadmap facilitates statistics planning and how to address the implementation of new technologies. The statement is supported since the lack of local roadmap is one of the reasons for the difficulties in identifying opportunities and suitable areas for Vanadium.

Argon deems that close collaboration with customers will be necessary for the future that requires new business models that extends the industrial value chain and increases the service. Lu et al. (2020) mention, with several Digital Twins that are connected through the manufacturing assets, people, and services the entire business can be virtually replicated and create a connected production network. If the connected production network consists of several Digital Twins across several factories, then there is an opportunity to connect the production network to trusted suppliers and customers. With the virtual model of the Digital Twin, connected between factories, the transparency and opportunities for collaboration are increased. According to Rasheed et al. (2020), the transparency and communication results in increased service and production of customized products since the connected Digital Twin contains extensive information regarding requirements and preference from stakeholders and market trends. When companies and their suppliers/customers connect their virtual production flows, the company can better adapt to changes in the supply chain. This can be used for instance if a delay occurs at the suppliers/customer's production, the company can be alerted in their Digital Twin system instead of the information going through various departments between the companies. A more efficient communication flow can be established where the company can take the change into account earlier.

Table 7 Summary of the analysis of organizational factors

Empirical findings	Theoretical findings	Analysis
An ambition to involve employees in changes and educate the personnel.	The organization strategy needs to encourage employees resource availability and readiness to achieve smart manufacturing (Nwaiwu et al., 2020). Using Digital Twin as a virtual training tool to educate personnel (Negri et al., 2017).	Developing and utilizing the employees' knowledge with Digital Twin that can visualize the company's assets. The result is better understanding of the equipment and opportunity to test solutions and provide feedback.
New business model will be required that extends the industrial value chain.	Digital Twin enables the creation of a connected production network to trusted suppliers and customers (Lu et al., 2020).	A company can adapt to changes in the supply chain by being alerted in their Digital Twin system. This will result in more transparency between organizations and a more efficient communication flow.

5.1.2. Operational factors

Unplanned stops are a mutual issue for the case companies, mostly due to difficulties with managing maintenance. For instance, the lack of efficient maintenance leads to a waste of resources for Argon. When the maintenance planning is based on assumptions, the frequency does not match the actual need for maintenance. A common goal for the case companies is to be able to perform condition-based and predictive maintenance. However, the lack of real-time data prevents this from being realized. The often-occurring unplanned stops for the case companies could be traced to the company's difficulties in finding the root-cause and the extent of when a problem transpires on the process level. This leads to the symptoms being treated and nothing prevents the same issue from arising again. The case companies have access to historical data but the problem of finding the root-cause could be connected to the difficulties of analyzing the data. The data that is available to analyze does not include data regarding the conditions over the machine, instead, the collected data consist of how many components were produced and under what parameters. This indicates the usefulness for companies to have a solution that records the machine's condition and then uses it as a basis for analysis. One solution that could be implemented is Digital Twin that connects the physical object with one-way real-time data to the virtual model that then responds to changes in the physical object. This type of Digital Twin is described by Kritzinger et al. (2018) as a Digital Shadow. Predictions could be made of the physical object's performance based upon continuously collected real-time data and historical data of the object's lifecycle (Negri et al., 2017). Companies need to be aware that numerous elements and interaction is required in the virtual model of the Digital Shadow to analyze machine's condition. This will result in that companies must manage complex models and algorithms. Although, the benefits from utilizing data-driven modelling to detect and fill the missing data is the possibility to predict the objects performance and thereby perform predictive maintenance (Aivaliotisa et al., 2019; D'Addona et al., Rasheed et al., 2020; Susto et al., 2015; Vathoopan et al., 2018). Prediction of possible failures could be made based on collected data irregularities, which can result in improved predictive maintenance and planning activities (Negri et al., 2017). The advantages of implementing such Digital Twin could result in the value of reduced waste regarding resources and time and increase traceability of fault sources since the Digital Twin is data-driven and based on facts (Lu et al., 2020). This could be beneficial since there is a mutual issue for the case companies to identify the root cause of a quality deviation. An obstacle of finding the root cause is the limited traceability in products and that measurement is performed within the tolerance. By using Digital twin, this challenge could be addressed since measurements are examine within the tolerances and can be linked to other data sources to identifying patterns to find fault sources. This may result in identifying new limits for the tolerance of the components and thereby enabling a reduction of quality deficiencies.

A common challenge for manufacturers is the high demand for personalized products, which is problematic since production systems are usually well established (Yin et al., 2018). This issue is reflected at Gallium since each of their orders are unique and personalized and causes difficulties in standardizing production flow and limits the flexibility. For manufacturing companies, there is a necessity to address the lack of flexibility to satisfy the changing demands of customers (Yin et al., 2018). According to Liu et al. (2019) and Lu et al. (2020), a way to tackle the issue with mass personalization in the manufacturing industry is to use Digital Twin to gain a clear image and insight to the performance of the manufacturing asset to increase the flexibility and resilience of the operations. This could be done by connecting multiple inputs to provide several alternatives for possible actions through processing the collected data with algorithms (Uhlenkamp et al., 2019). Since it is only necessary to have one-way connection with real-time data, Digital Shadow permits the performance of such actions. The numerous inputs can originate from multiple machines hence make the process more flexible when synergistic effects can be explored. The company can then better satisfy the changing demands from the customers by creating a more flexible process.

A result of having an Industry 4.0 is a dynamic and integrated system that enables collaborative planning, analysis, and implementation in an automated way (Lu, 2017). To achieve the collaboration vertical and horizontal integration and end-to-end communication is necessary at the operations (Chen, 2017; De Carolis et al. 2017; Lu, 2017). With the collaboration, the company can translate data into action and increase the value-adding activities (Lu, 2017). It has been observed that it is important for companies to translate data into actions to increase efficiency in the production flow. For instance, it would be useful for Argon to translate data into action by performing data analysis to optimize the production flow through optimal planning on where to produce which product. Which is possible to achieve with Digital Twin since production planning and control is a main application area. The data that the Digital Twin has processed and analyzed become structured statistical assumptions hence decisions regarding plan offers and orders can be improved (Rosen et al., 2015). When the data has been analyzed in the virtual model, decisions could increase in accuracy since the data has transformed into valuable information.

Table 8 Summary of the analysis of operational factors

Empirical findings	Theoretical findings	Analysis
Challenges with lack of real-time data that contribute to difficulties with performing accurate maintenance.	A connected manufacturing with machines equipped with smart objects which enables data-analysis (Li et al., 2017; Negri et al., 2017).	Digital Twin with accurate reflection of physical objects that can analyze the real-time data and thereby perform predictive maintenance.
Difficulties in satisfying high demand for personalized products due to well-established production system.	Companies need to have a flexible production flow to satisfy the changing demands from costumers (Yin et al., 2018).	Flexible process through exploration of synergistic effects in the Digital Twin to satisfy customers demands.
Future ambition to have the capability of translating data into action.	Achieve smart operation that allows for collaboration, integration and end-to-end communication (Chen et al., 2017; De Carolis et al., 2017; Lu, 2017).	Translate data into action through the Digital Twin's capability of analyzing the data and transforming it to valuable information.

5.1.3. Technological factors

Tao and Zhang (2017) and Xu et al. (2018) state that there is an opportunity with new advanced technologies and connectivity for the companies to improve their operational efficiency and productivity. The case companies assert that there are benefits of new technologies although it is important to first investigate the ability of the factory to support the implementation of new technologies e.g. suitable IT-structure, data management, and standardization. The statement of an extensive investigation is supported by Nwiawu et al. (2020), that it is important to plan how digital technologies can contribute to increasing competitiveness. Vanadium's mistake of implementing a change before the organization's maturity level was synchronized with the new technology resulted in a lack of value from the implementation which also strengthens the importance of a thorough investigation. The authors see an advantage in conducting a comprehensive investigation to determine the implementation scope and how to gradually introduce digital technologies.

To gain operational efficiency and to shift into a smart factory, new technologies that utilize a data-acquisition system, information- and network technology are needed. Infrastructure with advanced IT and IoT are essential to connect manufacturing assets to a smart factory (Tao, Qi et al., 2019) and with digitalization create a virtual factory (Negri et al., 2017). The virtual factory enables visualization of information for the employees to get a better overall understanding of the processes (Tao & Zhuang, 2017). The case companies realize that digitalization and more connected manufacturing is necessary to stay competitive and that the data needs to be better utilized and visualized for the employees. The key feature of connected manufacturing and realization of Industry 4.0 is integration and interoperability. To further take the advantages of the virtual factory and transform into Digital Twins, communication and collaboration between the machines are vital with real-time data (Lu, 2017). The collection of real-time data has been noted as a common challenge for the case companies, especially data connected to machine conditions and behaviors. However, the ability to collect real-time data on the condition and behavior of machines is an important part of Digital Twin in order to make informed decisions and thus create value (Lu et al., 2020; Qi & Tao, 2018; Wagner et al., 2019). This indicates a significant hurdle for manufacturing companies to overcome before Digital Twin can be successfully implemented. Another issue that has been observed is that an aging machine park hinders the ability to connect manufacturing assets and collect real-time data. The issue stresses the need for a plug-in solution to circumvent the obstacle of an aging machine park or a massive investment of time and money to replace a vast amount of manufacturing assets. This is noticeable in the fact that Gallium has changed its technical specification for purchasing new machines to include the ability to collect production data. It could also deduce that companies are preparing to find solutions to connect manufacturing assets. In the future, Argon believes that investment in new equipment ought to include a digital representation as well.

With digitalization, an increased amount of data is created from different sources, at different points in time and in different formats, which creates application islands and data silos. The data is difficult to use to the extent that is needed to create business value (Lin et al., 2019). This problem was expressed by the case companies that data silos are a common issue in manufacturing industries. The origin of data silos creates difficulties to search and navigate the data across multiple systems. A way to address the creation of silos is to implement Digital Twin. If the purpose is to reduce data silos the Digital Twin could be of a simpler version described as a Digital Model. This type of Digital Twin does not exchange any automated data with the physical object and therefore acts as a simulation model (Kritzinger et al., 2018). The Digital Model functions as a structured information source where data collected through different phases of a production system stays in one cohesive place (Negri et al., 2017). Hence, the virtual model only needs to manage information acquisition with the purpose of observing the physical object (Uhlenkamp et al., 2019). This can be interpreted as increasing accessibility of the data and thus more user-friendly since structured statistical data can be processed and analyzed. Thereby, the effectiveness of production planning, control and decision making can increase. Although, since the descriptive Digital Model does not respond to changes in the physical object, it is mostly a tool for assumed situations (Kritzinger et al., 2018). Companies need to consider that the decision is not founded in real-time conditions and changes might have occurred that alter the basis of the decision and how it needs to be addressed.

The case companies want to become more proactive to increase the availability of the machines and have better control over the equipment. To become proactive, companies need to use advanced technologies that can process high volumes of data and translate the data into business advantages (Lin et al., 2019). One way to facilitate this is through Digital Twin with a seamless connection of the CPS and digital world that will result in an optimized control over the system and future performance (Negri et al., 2017). It provides the possibility to optimize and adjust operations through one-to-one correspondence since the physical object and the virtual model have a similar appearance and the same behaviors (Tao, Qi et al., 2019). With the data integration in both directions it is possible to adjust the physical object through the virtual model and vice versa with real-time synchronization (Kritzinger et al., 2018). Since the virtual model can be accessible anywhere it is possible to use the Digital twin for real-time remote monitoring and control. Rasheed et al. (2020) state that it requires high computing power and fast communication in the IoT together with the Digital Twin's feedback mechanism. The scenario of executing remote monitoring and control is far in the future considering the case companies readiness towards smart manufacturing. If it were to be realized, companies that possess factories at several locations could perform monitoring and control from one location.

A Digital Twin with access to machine condition data, Big data processing, and Machine Learning provides the possibility to manage "what-if" situations, which can be useful to improve decision making (Barricelli et al., 2019). The intelligent Digital Twin can learn on its own with the use of Machine Learning and either initiate or execute an action with or without informing the users. It is an application that provides systems with the ability to automatically learn and improve from experience by identifying important patterns and changes (Uhlenkamp et al., 2019; Zhuang et al., 2018). The Digital Twin could then be of use to become more proactive, thus create value for companies where uptime for the machines is essential. If a factory becomes more proactive the potential issues can be identified sooner and be addressed before they arise. This can lead to fewer disruptions in the processes and increase production effectiveness. Aivaliotisa et al. (2019) and Vathoopan et al. (2018) mentions that an implementation of Digital Twin with data integration in both directions could result in a decrease in interruptions since the Digital Twin can correct issues without personnel interference. A possible outcome is more efficient maintenance with less unnecessary stops. The authors see a connection of higher uptime for the machines and more stable production with the outcomes of more efficient maintenance and production.

Table 9 Summary of the analysis of the technological factors

Empirical findings	Theoretical findings	Analysis
Challenges with synchronizing the implementation of new technologies with the organization's maturity level.	Important to plan how to use the new technologies to increase business competitiveness (Nwiawu et al., 2020).	Performing a comprehensive investigation that indicate implantation scope and how to gradually introduce digital technologies.
A common issue for manufacturing companies is the creation of data silos.	Digital Twin enables structed information and data storage to stay in one cohesive place (Negri et al., 2017).	The Digital Twin facilitates the processing and analyzing of structed statistical data to increase effectiveness of production planning and control.
A common ambition is to become more proactive to achieve higher availability and control over the equipment.	Beneficial for companies to use advance technologies such as Digital Twin, that can process high volume of data and translate the data into business advantages (Lin et al., 2019; Negri et al., 2017).	Using Digital Twin with machine learning to achieve advantages of being proactive by enabled control of the physical object and identifying important patterns.

5.2. Assessing a shop-floor Digital Twin

In the following section, the analysis is designed to process the second research question, which concerns the evaluation of Digital Twin in a shop-floor. The purpose is to identify certain requirements for companies and in their shop-floors to tackle challenges to achieve smart manufacturing and create the capability to implement Digital Twin. To understand what effect and change the implementation of Digital Twin on a shop-floor will bring, a real case of a production cell at Argon was examined. Through the empirical findings and the collected theory, an analysis of shop-floor management, physical shop-floor and shop-floor service system was conducted to address how Digital Twin technology can work as an effective convergence between the physical and virtual space. Figure 5 visualizes the findings of the analysis on the assessment of Digital Twin in the shop-floor at Argon and will be describe in the following sections.

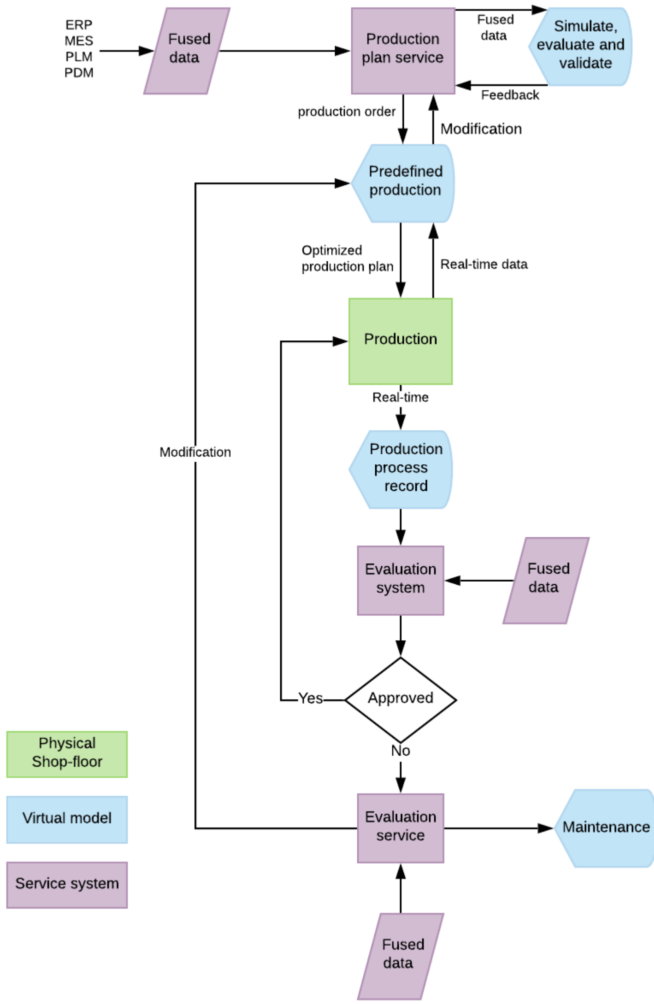

Figure 5 Process map of Argon's future shop-floor with Digital Twin implemented

5.2.1. Shop-floor management & shop-floor Digital Twin

New advanced technologies such as IoT, Machine Learning, cloud computing and Digital Twin allow factories to evolve into smart and collaborative manufacturing (Liu et al., 2019; Qi & Tao, 2018). To achieve smart manufacturing, shop-floor management and control must go through the same change towards integrated-, collaborative and smart management (Zhuang et al., 2018). Managing the shop-floor effectively is essential to achieve high production efficiency, low product cost and high product quality. Since the shop-floor is a convergence point with information flow, material flow, and control flow, the company can face difficulties in choosing the right management and control methods (Zhuang et al., 2018). Currently, the production planning department at Argon gets information regarding the status of material stock and assumed production time for the orders and is used to create biweekly production orders for the shop-floor. The production orders are communicated to the preplanned production service through weakly meetings and non-electronic documents from the ERP system. According to Zhuang et al. (2018), the inability to perform electronic data acquisition is an obstacle in achieving more efficient shop-floor management.

Argon sees an opportunity with digitalization to increase the productivity of production planning and reduce the amount of paper documentation. Currently, the production planning is estimated from assumed cycle times and expected capacity. The production planning gets feedback from the physical shop-floor with the actual production time when the production order is produced. If the actual production time does not correspond with the assumed time, correction of pricing and production planning is made to align with the accurate information. However, the data regarding cycle times that are received from the physical shop-floor is difficult to interpret since the data is in the form of minutes that the machine has been running instead of produced number of articles. If Argon would implement Digital Twin, the physical objects and associated data e.g. working progress, working status of stations and manufacturing resources will be mapped in a virtual space (Tao & Zhang, 2017; Zhuang et al., 2018). Therefore, smart interconnection and interoperability could be achieved (Tao & Zhang, 2017) since the Big data exchange data, information and, knowledge between physical and virtual space and is stored and managed in a service platform where the incoming data could be analyzed (Zhuang et al., 2018). In Argon's case, the transition would be from an Andon system with data that is visualized from the ERP system to a future state, shown in the upper part of figure 5, were Digital Twin utilizes fused data from the service system. The virtual model of the Digital Twin can use the fused data to simulate, evaluate and validate the physical system since the Digital Twin can monitor and track the physical shop-floor continuously (Zhuang et al., 2018). The analysis of production data and product specification will assist in optimizing production planning and strategy since the Digital Twin provides an accurate overview of the shop-floor capacity and resources. The virtual model's feature could also be utilized for the benefit of achieving virtual commissioning through simulating and validating the production data. The virtual model can then function as a tool for testing and verifying decisions before implementing eventual changes on the shop-floor.

By utilizing the Digital Twin in the shop floor, Argon's approach of optimizing the production sequence will change. Instead of having the preplanned production service that uses Excel as a service tool, the optimal production plan can be designed with the Digital Twin's ability of integration planning. The integrated planning is enabled since the Digital Twin can use different sources to identify bottlenecks and capacity (Biesinger et al., 2019). By analyzing the data and capacity of the shop-floor in the virtual model, the production sequences that create bottlenecks can be prevented. This is visualized in figure 5 as the creation of a virtual model for predefined production, were the production order can be transmitted digitally to the HMI in the physical shop-floor and alert if modifications are needed in the production plan service based on real-time status.

5.2.2. Physical shop-floor

Currently, Argon does not analyze any real-time data from the physical shop-floor. However, they can collect data which has been generated from the PLCs, although there is no feasible approach at the moment to create any valuable information from that data. The reason is partly because the data must be manually entered in Excel and lack of resources to analyze the collected data. Tao and Zhang (2017), emphasize that the physical shop-floor need to be connected with smart objects, actuators and controllers to enable real-time communication, protocol standardization and integration. Shop-floor Fieldbus and Industrial Ethernet are usually implemented to accomplish this (Lu et al., 2020; Tao & Zhang, 2017). An important part of being able to capture real-time data is to connect manufacturing assets to RFID, Auto-ID and embedded sensors. Thus, becoming smart objects that creates signals of operational data to the Digital Twin, which enable detection of real-time changes as well as identification and tracking of the object through the production process (Guo et al., 2020; Leng et al., 2019; Tao & Zhang, 2017). Another advantage with smart objects is the possibility of collecting data regarding equipment's status and operation, personnel status data and production logistical data (Zhuang et al., 2018). The collection of this data would be beneficial for Argon to improve efficiency at the shop-floor by enabling the calculation of OEE. With increased knowledge regarding equipment's status, companies gain a more thorough understanding of the utilization degree of their operations and can identify optimization opportunities. However, a common issue to access smart object data to the virtual space is the different interfaces and communication protocols (Tao & Zhuang, 2017). A solution to solve the communication problem is to use neutral "language" standards e.g. MTConnect (Coronado et al., 2018; Tao & Zhang, 2017). This makes it possible to collect data from machine tools and thereby smart objects can be shared and managed in digital space (Coroando et al., 2018; Guo et al., 2020). The data from the smart objects, such as objects ID, attribute and current status can be synchronized with real-time data from the manufacturing status through the Digital Twin. This enables valuable information to become visualized and traceably in the virtual system of the Digital Twin (Guo et al., 2020). Which is in accordance with the case company's ambition to have an approach to create value from real-time data. This will reduce the need for handling data manually to Excel by using Digital Twin with structured and more comprehensive data collection. The result is the possibility to analyze the data into valuable information that can function as a service for the physical system.

5.2.3. Shop-floor service system

The ERP system provides information regarding article numbers, order numbers, batch size, and process flow and is a fundamental part of the service system at Argon. If Digital Twin is implemented at Argon, the service system needs to expand with additional information systems such as MES, PDM and PLM. The service system could then provide fused data to support the evaluation performed by the virtual model which then can validate and verify the shop-floors accuracy to control and increase efficiency at the physical shop-floor (Coronado et al., 2018; Leng et al.,2019; Zhuang et al., 2018). The virtual model of the Digital Twin contains information regarding geometry, physical aspects, behaviors and rules (Tao & Zhang, 2017; Zhuang et al., 2018). The geometry data is comprised of data regarding shapes, sizes, position and assembly relations of machine components (Tao & Zhang, 2017). At Argon, this information originates from CAD/CAM.

The physical aspect that needs to be included in the virtual model is collected from physical attributes from the shop-floor (Tao & Zhang, 2017). Sensors are needed in the shop-floor to capture such data, which Argon do not possess. In the future state, sensors that collect data regarding attributes e.g. temperature, pressure, force, position, and capacity need to be implemented.

The behavior that is needed for the virtual model of the physical system is a thorough description of how the machine responds under driving factors (Tao & Zhang, 2017). Currently, the NC-code of behaviors is manually entered by the operators in the shop-floor at Argon. To analyze the behavior of the physical system, rules of association, constraints, and deduction need be applied in the virtual model of the Digital Twin (Tao & Zhang, 2017). The virtual model also needs model service. e.g. Machine Learning, neural network and data mining to provide prediction that can lead to the possibility of autonomous decisions (Zhuang et al., 2018). The optimized result can yield feedback to the production plan service and thereafter the improvement can be transmitted to the physical system (Leng et al., 2019). Figure 6 provides an overview of the components that would be included in the virtual model of the Digital Twin in Argon's case.

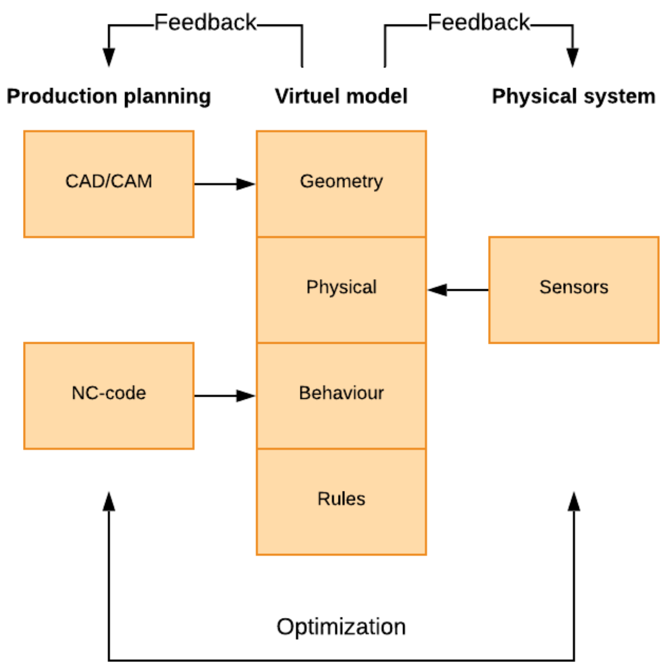

Figure 6 Illustration of virtual model

With the implementation of Digital Twin in the shop-floor, the service system facilitates communication between the physical system and the production plan service. The data and information exchange must transpire without any delay (Rasheed et al., 2020). To achieve low latency with information exchange, Argon needs to use an MES. Mainly because the ERP system is not sufficient to handle activities that require quick response such as real-time monitoring and control. With the MES the production order can be directly transmitted to the HMI, hence the need to manually enter NC-code and prescription can be eliminated. This can have a positive effect on the stability in the shop-floor since the human error that occurs through manual handling can be reduced. It will also raise the degree of digitalization since less paper needs to be transmitted between the different departments. Although, Coronado et al. (2018) mention that some of the current MES have limitation in dealing with real-time capability and interoperability issues and thereby manually entered data may still be needed. According to Jeon et al. (2017), this stresses the need for a smart MES architecture with infrastructure for real-time communication, data integration and transformation, the ability to handle Big data and synchronized functionality modules. This signifies the importance to include necessary capabilities in an MES to support the high utilization of the Digital Twin. Therefore, the case company needs to be thorough when the specification requirements of an MES system is designed.

The fused data from the service system could optimize quality control at the shop-floor since the Digital Twin can identify patterns and trends (Tao & Zhuang., 2017). This can be performed through structured high-quality data that has been cleaned from the noise of incoming raw data (Lu et al., 2020; Qi & Tao, 2019; Tao & Zhang, 2017). Data cleaning is important so that the noise does not contribute to misleading results in the data analysis (Lu et al., 2020). By performing data mining, Big data analytics and Machine Learning on data from different sources, a more extensive interpretation are created through advanced data analytics (Lu et al., 2019; Tao & Zhang, 2017). Argon's problem with residual material on their articles could be reduced with a more extensive interpretation of equipment's condition and the performance at the shop-floor. The knowledge of the equipment's condition and the production process record will be stored in the virtual model of the Digital Twin. This can result in the identification of root-causes and the ability to perform predictive maintenance, due to more comprehensive and analyzed data from multiple sources in the service system. Currently, they cannot perform predictive maintenance since the current maintenance is not determined from data of the service system, instead, the planned maintenance is performed based on experience and recommendation. Through the Digital Twin's capability to use an evaluation system to predict maintenance by detecting deviations from patterns and trends, automated and continuous quality control can be achieved instead of frequency-based quality control. With the fused data and the advanced data analytics, evaluation service can be performed to determine if the deviation is due to inaccurate settings in the machines or if maintenance is required. If the deviation is due to inaccurate settings, a modification to the predefined production is needed to adjust the machine settings, as shown in figure 5. The Digital Twin can then change the physical system according to the modification. In an optimal state with Digital Twin implemented, predictive maintenance can be executed at Argon that does not interfere with the production system and remove the need for destructive tests. This is possible if the Digital Twin can perform highly accurate condition monitoring and control of the physical shop-floor.

6. CONCLUSIONS AND RECOMMENDATIONS

To know what benefits Digital Twin can provide in form of increased business value, the analysis was designed to identify applications within the Digital Twin and which approaches are necessary to achieve those applications, thereby the first research question can be answered. To realize the values of Digital Twin, it is necessary for the second research question on what changes in the shop-floor need to be done to implement Digital Twin to be answered. In this chapter the findings of the analysis will be presented.

- *RQ1: How can Digital Twin be beneficial to increase business value in a manufacturing company?*

To be able to decide what benefits Digital Twin could yield to manufacturing companies it is important to first have a clear understanding and definition of Digital Twin. However, there is confusion in both research and industry what unifies Digital Twin. A conclusion can be made by examining the definitions that there are two major different distinctions. One distinction presses the necessity to be able to collect real-time data to be referred to as a Digital Twin, while the other does not address it as a requirement. However, this limit is not sufficient enough since even though the Digital Twin can generate real-time data, there are significant variations in features. With the conducted literature review, discoveries have been made that Digital Twin can be described in various ways but still be defined as a Digital Twin. For example, Digital Model and Digital Shadow are referred to as Digital Twin despite the difference in data integration between the concepts, which in turn results in broad differences for what the digital technologies require. For this reason, the definition should be based on the degree of data integration since that controls the Digital Twin's functions, see table 10. To avoid confusion, a more descriptive definition of Digital Twin is necessary to make the concept more concrete. Since the name "twin" associates with two parties that are a replica of each other, the term should also include requirements of two-ways data integration, e.g. changes in the physical object affect the virtual model and vice versa. Therefore, Digital Model and Digital Shadow should not be defined as Digital Twin, instead, they should be two separate concepts. This will result in clearer discussions and fewer misunderstandings on potential opportunities with the Digital Twin.

Table 10 Definition analysis

	Digital Model	Digital Shadow	Digital Twin
Definition analysis	Physical and virtual part and interaction through manual data transfer.	Physical and virtual with one-way real-time interaction.	Physical and virtual with two-way real-time interaction.

By devising the concept into more descriptive character, the identification of possible benefits of Digital Twin is facilitated. For example, a manufacturing company with low readiness for digitalization who is not able to implement Digital Twin may benefit from the implementation of Digital Models. It is important to start small and then when the organization is ready more advanced technology can be included. This is to adapt the degree of digitization to the readiness of the organization, operation and employees. The Digital Model could be used as a training and project tool to develop and utilize the employees' knowledge. This will enable extensive testing and thorough scrutinizing before the implementation phase of a project. Additionally, Digital Model can be utilized for production planning and control by processing and analyzing structured statistical data. With Digital Model, the analyzed data is stored in one cohesive place and can transform the data into accessible and user-friendly information to base decisions on.

With a higher maturity level of digitalization, it is possible to implement a more complex digital technology that could be described as Digital Shadow. All previously mentioned applications are included in Digital Shadow but with the ability to react on changes from the physical object with real-time connection the application areas expand. With connection through the entire organization and end-to-end communication, collaboration between different departments is possible. This facilitates production planning and control since data can be translated into valuable information to take action from, which can improve decisions regarding the planning of orders. The Digital Shadow collects real-time data regarding machine status and condition, thereby predictive maintenance is feasible. The result leads to efficient maintenance and planning through increased traceability of fault sources. The collection of real-time data and the ability to react on changes from the physical object creates an opportunity to use the virtual model of the Digital Shadow as a training and project tool with real-time data to base interaction from to create an understanding of real scenarios. Another application with Digital Shadow is for personalized products and changing demands of customers since the Digital Shadow can take actions with several inputs into account. This enables a flexible process through an exploration of synergistic effects and therefore the company can gain higher customers satisfaction. It is also possible for manufacturing companies to have a connected production network of Digital Shadows across suppliers and customers. By a shared virtual model of the Digital Shadow, companies can be alerted to changes that occur at different parts of the network hence adapt the production flow to the changes in the supply chain. The connected production network will enable better transparency and communication with suppliers and customers which can result in better services while a reduction of waste regarding resources and time could be accomplished. Due to the company being alerted on eventual changes at suppliers and customers that could affect the manufacturing, the company can adjust its production plan accordingly.

The highest complexity is achieved with Digital Twin that requires a developed IT-structure, data management and standardization. The Digital Twin with a seamless connection between the physical and virtual world enables the companies to become proactive since the Digital Twin can process high volumes of data and transform the data into business advantages. The Digital Twin encompasses the application areas for the Digital Model and Digital Shadow together with the ability to manage "what-if" situation and the possibility of real-time remote monitoring and control. By incorporating machine learning, important patterns and changes could be identified and used to adjust the physical object of the Digital Twin. To enable real-time remote monitoring and control the company needs to possess high computing power along with fast communication in the IoT. The company could then monitor and control factories at several location from one location. Whether the Digital Twin is used within one or several factories, the production system can be optimized with less disruption and higher machine-uptime with the Digital twin's feedback mechanism. Further application scope for the Digital Twin is not fully explored due to manufacturing companies' maturity level is limiting the ability to implement Digital Twin. Since the Digital Twin is closer akin to the engineering category and industrial practice, research on further application areas are hindered. This was strengthened by the empirical finding of the limited manufacturing maturity of digitalization. Therefore, it is recommended for manufacturing companies to first achieve Digital Model and then Digital Shadow before attempting to implement Digital Twin. Applications, approaches and values of the three different digital technologies are presented in table 11. The development of digital technologies is successively based on previous levels. This means that the Digital Twin will receive the same applications and value as Digital Model and Digital Shadow. However, more value will be included as the technology is more advanced and the virtual model contains several features. With the increased features, more elements and interactions are required, resulting in more complex models and algorithms for the virtual model.

Table 11 Compilation of Digital Model, Digital Shadow and Digital Twin

	Application	Approach	Value
Digital Model	Training and project tool.	Simulating scenarios to test solutions and enable feedback from the operators.	Developing and utilizing the employees' knowledge.
	Production planning and control.	Using one cohesive place to process and analyze structed statistical data.	Accessible and user-friendly information to base decisions on.
Digital Shadow	Training and project tool.	Interaction of physical object in a virtual model based on real-time data	Increased stability of the production processes with comprehensive understanding of real scenarios and prediction of manufacturing assets.
	Production planning and control.	Translate data into action.	Increased value-adding activities and improved decision regarding planning of orders.
	Predictive maintenance.	Analyzing the collected real-time data relating to machine status and condition.	Efficient maintenance and planning through increased traceability of fault sources.

	Personalized products and changings demand.	Flexible process through exploration of synergistic effects.	Higher customers satisfaction.
	Collaboration with suppliers and customers through connected production network.	Increase the transparency and communication and facilitate adapting to changes within the connected production network supply chain.	Increase service for supplier and customers while reducing waste regarding resources and time.
Digital Twin	Scenarios and risk assessment to manage "what-if"-situation.	Adjust the physical object and identifying important patterns and changes with utilization of machine learning.	Less disruption and higher machine-uptime resulting in an optimized and proactive production system.
	Real-time remote monitoring and control.	Possess high computing power along with fast communication in the IoT.	Monitor and control several factories at different location from one place.

- *RQ2: What requirements in the shop-floor is necessary to implement Digital Twin?*

Table 11 highlights the possible values of Digital Twin, however, to realize those values, companies need a certain structure and supporting equipment. There is not a plug-in-solution to implement a Digital Twin in the present, instead, companies need to achieve some degree of smart manufacturing to have the ability to use Digital Twin technologies. To achieve smart manufacturing, the shop-floor management and control and the shop-floor manufacturing need to undergo the same change towards becoming integrated, collaborative and smart. Shop-floor is a convergence point with control-, information-, and material flow. Hence, these must be considered and adapted to implement Digital Twin in the shop-floor. It is necessary for the control flow to go from a separated and unconnected flow that transpires manually to a continuously and real-time updated flow so that integrated planning is possible. It is important for the information flow to be expanded to include a wider spectrum of data e.g. geometry, physical aspects, behaviors and rules. Therefore, it is essential that the information system in the shop-floor includes an ERP system, MES, PDM and PLM. To create a value of the information to the shop-floor, a developed evaluation system is vital. In the Argon's situation, it would mean transitioning from using Excel to a virtual model in the Digital Twin that can perform data mining, Big data analytics and Machine Learning. The fused data in the virtual model could then optimize shop-floor management and production planning. To use the full potential of the Digital Twin technology, the physical system should be designed to enable real-time communication between machine-to-machine and machine-to-human. To qualify the communication, the manufacturing objects in the shop-floor must be transformed into smart objects that can create and send signals in a neutral language. Hence, the virtual model can capture and use the data from the physical shop-floor regarding equipment- and production status.

By combining the research questions, a more comprehensive knowledge regarding the amount of work that is required to implement Digital Twin compared to the value that will be created is obtained. A great amount of effort is necessary to create the foundation of data collection and integration in the beginning phase of implementing Digital Twin. However, when the Digital Twin can be utilized, companies can achieve all the presented business value since the derived value from Digital Model and Digital Shadow is accumulated in Digital Twin, as shown in figure 7.

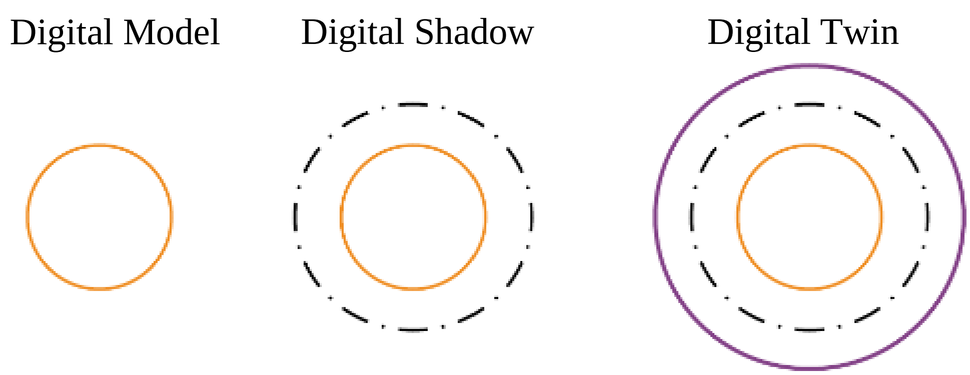

Figure 7 Value circles

To strengthen the findings in this thesis, a recommendation for future studies is to involve more case companies to increase the validity of the empirical findings. Additionally, to reassert the validity of the performed assessment of Digital Twin in the shop-floor and the values that are created, a recommendation is to conduct a proof of concept to evaluate the applicability. It would be useful for future research to examine a plug-in solution for Digital Twin, due to the difficulties to generate and collect real-time data from aging machine parks and production systems that currently exist in manufacturing industries.

The authors have reached an understanding that a great amount of effort is required to reach the fundamentals of Digital Twin, both in time and resources. An interesting research question would be about measuring resources and effort in relation to created value. This would require studying the phenomenon over a long period of time in order to measure resource consumption and then perform a comparison with the created business value.

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8. APPENDICES

Appendix 1 – Interview guide (Swedish)

Appendix 1 - Interview guide 1 (Swedish)

Intervjuguide 1

Examensarbete 30 hp inom produktion och logistik på Mälardalens högskola

Integritet och sekretess

- Varje företag och respondent kommer benämnas anonymt i rapporten
- När studien är slutförd kommer all information och ljudfiler raderas
- Respondenten är fri att avböja att svara på frågor under intervjun
- Slutgiltiga examensarbetet kommer att publiceras på DIVA

Övrig information

- Intervjuerna kommer att spelas in
- Intervjun förväntas ta cirka 1 timme

Begrepp som kommer att användas under intervjun

Industri 4.0
Den fjärde industriella revolutionen där framtidens tillverkande företag är självstyrande smarta fabriker med ännu effektivare produktion och logistik. Den tekniska grunden ligger i intelligenta digitala nätverkssystem där maskiner och produkter kommunicerar med varandra genom Internet of Things

Spårbarhet
Spårbarhet innebär att fullständig information för varje steg i en processkedja finns tillgänglig. Det innebär att varje händelse av betydelse i processen är verifierbar och går att härleda.

Introfrågor

- Vad är din titel?
- Vilka är dina ansvarsområden?

Nuläge

1. Hur jobbar ni för att hålla er konkurrenskraftiga på marknaden?
    a. Vilka är era största utmaningar på företagsnivå?
2. Hur har industri 4.0 en roll i er produktionssystemutveckling?
3. Har ni någon utformad digitaliseringsstrategi?
4. Vilka nya teknologier arbetar ni med idag?
    a. Vad finner ni får utmaningar med de nya teknologierna?
    b. Vilket värde bidrar de nya teknologierna med?

Framtid

5. Vad är er vision för den här fabriken?
    a. Vad har ni för strategier för att nå målet? (långsiktigt/kortsiktigt)

Organisation

6. Hur planerar ni inför förändringsarbete?
    a. Hur involverar ni operatörer i förändringsarbete?
    b. Hur arbetar ni med kompetensutveckling mot industri 4.0?

Process

7. Berätta lite kort om processen?
    a. Vilka är era största utmaningar på processnivå?
8. Hur arbetar ni med kvalitetssäkring?
    a. Hur hanteras uppföljningen av avvikelser?
    b. Hur återkopplas avvikelser till tillverkningsprocessen?
9. Hur arbetar ni med spårbarhet i er fabrik?
10. Är det vanligt med oplanerade stopp på produktionsgolvet?
    a. Följs det upp, och hur?
11. Vad har ni för visioner för processen?

Teknologi

Data

12. Hur arbetar ni med digitalisering av produktionsdata?
13. Hur samlas data in?
14. Hur sparas data?
15. Hur pass sökbar är data?

Digital tvilling

16. Vad är en digital tvilling enligt er?
17. Har ni någon form av digital tvilling i dagsläget?

Appendix 2 - Interview guide 1 (English)

Interview guide 1

Master thesis, 30 hp within production and logistics from Mälardalen University

Privacy and confidentiality

- All participating companies and respondents will be referred to anonymously in the thesis
- When the study is concluded all of the audio files and other collected information will be deleted from the authors devices
- The respondent is free to decline answering any questions at their discretion during the interview
- The final report will be uploaded to DIVA

Other information

- The interview will be audio recorded
- The interview is expected span 1 hour

Terms and concepts that will be used during the interview

Industry 4.0
The fourth industrial revolution, where the manufacturing companies of the future are self-managed smart factories with even more efficient production and logistics. The technical foundation lies in intelligent digital networking systems where machines and products communicate with each other through the IoT.

Traceability
Traceability means that full information for each step in a process chain is available. This means that every significant event in the process is verifiable and can be deduced.

Intro questions

- What is your title at the company?
- What are your responsibilities?

Current state

1. How do you work to stay competitive in the market?
    a. What are your uttermost challenges at company level?
2. How does industry 4.0 play a role in your production system development?
3. Do you have a formulated digitization strategy?
4. What new technologies do you work with today?
    a. What do you find challenging with the new technologies?
    b. What value do the new technologies contribute with?

Future state

5. What is your vision for this factory?
    a. What strategies do you have for reaching that goal? (Long term / short term)

Organizational

6. How do you plan before implementing change?
    a. How do you involve operators in changes that are going to be made?
    b. How do you work with competence development towards Industry 4.0?

Operational

7. Tell us a little about the process?
    a. What are your biggest challenges at process level?
8. How do you work with quality assurance?
    a. How are the follow-up on detected deviations handled?
    b. How are the follow-up on detected deviations reconnected to the manufacturing process?
9. How do you work with traceability in the factory?
10. Is the occurrence of unplanned stops common on the shop-floor?
    a. Is there follow-up on the unplanned stops and how is that performed?
11. What is your vision for the process?

Technological

Data

12. How do you work with digitalizing the production data?
13. How is production data collected?
14. How is the collected data stored?
15. How searchable is the collected data?

Digital Twin

16. What is a Digital Twin according to you?
17. Does some form of a Digital Twin exist in your factory today?

Appendix 3 - Interview guide 2 (Swedish)

Intervjuguide 2

Examensarbete 30 hp inom produktion och logistik på Mälardalens högskola

Integritet och sekretess

- Varje företag och respondent kommer benämnas anonymt i rapporten
- När studien är slutförd kommer all information och ljudfiler raderas
- Respondenten är fri att avböja att svara på frågor under intervjun
- Slutgiltiga examensarbetet kommer att publiceras på DIVA

Övrig information

- Intervjuerna kommer att spelas in
- Intervjun förväntas ta cirka 1 timme

Intro fråga

- Vi vill gärna ta del av en processkarta över tillverkningsprocessen om det finns i dagsläget?

Appendix 3 – Interview guide (Swedish)

Produktionsplanering

1. Hur säkerställs produktionsplanering?
2. Hur optimerar ni produktionsplanering?
3. Hur registreras en order för cellen?
4. Hur sker kommunikationen av produktionsplaneringen till shop-floor?

Datainsamling och datahantering

5. Vilken input data genereras till cellen? (Exempelvis materiallager status, utrustningskapacitet)
6. Vilken data genereras av cellen? (Exempelvis typ av realtidsdata och OEE-data)
    a. Hur vidarebefordras datan?
    b. Hur sparas och hur används datan?
7. Finns det sensorer i cellen?
    a. Vilken data samlar den upp?
8. Vilken typ av data baseras de planerade underhållen på?
    a. Vart kommer den datan ifrån?
    b. Hur dokumenteras åtgärderna som gjort under de planerade underhållen?
    c. Hur används dokumentation för planering av framtida underhåll?

Utvärderingssystem

9. Hur jobbar ni för att optimera processen?
    a. Vad har ni för data analysverktyg?
10. Hur plockas avvikelserna upp?
    a. Hur registreras den data?
    b. Hur används datan?
    c. Hur vidare kommuniceras den analyserade datan?
11. Hur sker kvalitetssäkringen i cellen?
    a. När sker det och hur ofta?

Övriga frågor

12. Används några visualiseringsverktyg i dagsläget?
    a. Om ja, på vilken sätt?
        i. Vilken data blir visualiserad?
13. Hur går produktionsprocessen till i cellen?
    a. Vad tillverkas?
    b. Vilka processteg ingår i cellen?
    c. Vad består cellen av? (maskiner, robotar, sensorer, PLC, MES, ERP)
    d. Vilka utmaningar finns på dem separata processtegen?

Appendix 4 - Interview guide 2 (English)

Interview guide 2

Master thesis, 30 hp within production and logistics from Mälardalen University

Privacy and confidentiality

- All participating companies and respondents will be referred to anonymously in the thesis
- When the study is concluded all of the audio files and other collected information will be deleted from the authors devices
- The respondent is free to decline answering any questions at their discretion during the interview
- The final report will be uploaded to DIVA

Other information

- The interview will be audio recorded
- The interview is expected span 1 hour

Intro question

- If there exists a process map of the manufacturing process, is it possible for you to share it with us?

Production planning

1. How is the production planning performed?
2. How is the production planning optimized?
3. How are the orders registered in the cell?
4. How is the production plan communicated to the shop-floor?

Data collection and data management

5. What input data is generated for the cell? (For example, material stock status, equipment capacity)
6. What data is generated by the cell? (For example, kind of real time data and OEE-data)
    a. How is the data forwarded?
    b. How is the data stored and used?
7. Are there sensors in the cell?
    a. What data do the sensors register and collect?
8. What type of data is the planned maintenance based on?
    a. Where does that data originate from?
    b. How are the planned maintenance measures documented?
    c. How is that documentation used for planning future maintenance?

Evaluation system

9. How do you work to optimize the process?
    a. What tools are used for data analysis?
10. How are deviations detected?
    a. How is that data registered?
    b. How is the data over deviations used?
    c. How is the analyzed data further communicated?
11. How is the quality assurance performed in the cell?
    a. When and how often is it performed?

Other questions

12. Are any visualization tools used at the present?
    a. If yes, in what way?
        i. What data is visualized?
13. Could you describe the manufacturing process in the cell?
    a. What is made in the cell?
    b. What process steps are performed?
    c. What is the cell made up of? (machines, robots, sensors, PLC, MES, ERP)
    d. What challenges exist in the separate process steps?