THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

From Data to Decision Support in Manufacturing

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ABSTRACT

Digitalization is changing society, industry, and how business is done. For new companies that are more or less born digital, there is the opportunity to use and benefit from the capabilities offered by the new digital technologies, of which data-driven decision-making forms a crucial part. The manufacturing industry is facing the Fourth Industrial Revolution, but most manufacturing organizations are lagging behind in their digital transformation. This is due to the technical and organizational challenges they are experiencing. Based on this current state description and existing gap, the vision, aim, and research questions of this thesis are:

> **Vision -** future manufacturing organization to be driven by fact-based decision support based on data rather than of relying mainly on intuition and experience.
> **Aim -** to show manufacturing organizations the applicability of digital technologies in digitalizing manufacturing system data to support decision-making and how data sharing may be achieved.

> **Research Question 1.** How do manufacturing system lifecycle decisions influence the requirements of data collection towards interoperability?
> **Research Question 2.** What makes interoperability standardization applicable to sharing data in a manufacturing system's lifecycle?

This research is applied, addressing real-world problems in manufacturing. For this reason, the main objective is to solve the problem at hand, and data collection methods will be selected that can help address it. This can best be explained by taking a pragmatic worldview and using mixed methods approach that combines quantitative and qualitative methods. The research upon which this thesis is based draws on the results of three research projects involving the active participation of manufacturing companies. The data collection methods included experiments, interviews (focus group and semi-structured), technical development, literature review, and so on.

The results are divided into three areas: 1) connected factory, 2) standard representation of machine model data, and 3) the digital twin in smart manufacturing. Connected factory addresses the question of how a mobile connectivity solution, 5G, may be used in a factory setting and demonstrates how the connectivity solution should be planned and how new data from a connected machine may support an operator in decision-making. The standard representation of machine model data demonstrates how an international standard may be used more widely to support the sharing and reuse of information. The digital twin in smart manufacturing investigates the reasons why there are so few real-world examples of this.

The findings reveal that a manufacturing system's lifecycle impacts data requirements, including a need for data accuracy in design, speed of data in operation (to allow operators to act upon events), and availability of historical data in maintenance (for finding root causes and planning). The volume of data was identified as important to all lifecycles. The applicability of standards was found to depend on: 1) the technology providers' willingness to adapt standards, 2) enforcement by OEMs and larger actors further down a supply chain, 3) the development of standards that consider the user, and 4) when standards are required for infrastructure reasons.

Based on the results and findings obtained, it may be stated that it is important to determine what actual manufacturing problem should be addressed by digital technology. There is a tendency to view this change from the perspective of what the digital technology might solve (a technology push), rather than setting aside the solution and focusing on what problem should be solved (a technology pull). This work also reveals the importance of the collaboration between industry and academia making progress in the digital transformation of manufacturing. Proofs-of-concept and demonstrators of how digital technologies might be used are also important tools in helping industry in how they can address a digital transformation.

Keywords: digitalization, data-driven decision-making, interoperability, standards, manufacturing system lifecycle, Industry 4.0, Smart Manufacturing, 5G

ACKNOWLEDGEMENTS

This PhD thesis compiles the work that I have done during the five years as a PhD Student at the division of Production Systems at Chalmers University of Technology. Since I started my PhD journey, I have for sure learned more about the production area, but also how to become a researcher. This journey has been accompanied by numerous people and I would like to acknowledge those persons here for their contribution.

First and foremost, *Professor Björn Johansson* and *Professor Johan Stahre*. You were willing to give me this opportunity to join your group spring 2016. Since then you have challenged me both in my work and my research. You have provided me with interesting opportunities and given me responsibility where you have trusted me to be able to follow through and succeed. At the same time, you have always been available as support and persons I could go to for advice and recommendations. Thank you!

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My research and results depend on the research projects that I have been involved in including the projects:

- *The Space Industry of Tomorrow* in collaboration with *RUAG Space AB* funded by NRFP;
- *5G Enabled Manufacturing (5GEM)* in collaboration with *Ericsson AB* and *SKF AB*, funded by the Swedish Agency for Innovation Systems (VINNOVA) and their strategic program for sustainable Swedish production (Produktion 2030);
- *BOOST 4.0* involving numeours industrial partners all over Europe and EU-funded;
- *Digitala Stambanan* involving numerous industrial partners and funded by VINNOVA;
- *4S* funded by VINNOVA (the project work also involved engagement in the technical committees SIS TK 280 and ISO/TC 184 SC 4 JWG 15); and
- *Area of Advance Production* at Chalmers University of Technology

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Maja Bärring
Gothenburg, September 2021

APPENDED PUBLICATIONS

Paper 1 **Bärring, M.**, Johansson, B., & Stahre, J. (2020). Digital Technologies Enabling Data of Production Systems for Decision Support. *Smart and Sustainable Manufacturing Systems*, 4 (2), 62-79. https://doi.org/10.1520/SSMS20190034

Contribution This paper was a result of the Licentiate thesis and it relies on results from Project A (5GEM). Bärring was the first author of the paper with support from main supervisor, Johansson, and co-supervisor, Stahre.

Paper 2 **Bärring, M.**, Iupikov, O., Alayon Glazunov, A., Ivashina, M., Berglund, J., Johansson, B., Stahre, J., Engström, U., Harrysson, F., & Friis, M (2021). Factory Radio Design of a 5G Network in Offline Mode. *IEEE Access*, 9, 23095-23109. http://dx.doi.org/10.1109/ACCESS.2021.3055941

Contribution This paper presents the work of developing a new offline procedure to plan a wireless network, 5G, for a factory environment. Bärring was first author of the paper, leading and distributing the writing among the co-authors. Also involved in developing and performing the study together with partners from Chalmers, Ericsson and SKF. Iupikov, Glazunov, and Ivashina performed the ray-tracing simulation, Harrysson and Engström the network measurements, Bärring and Berglund the virtual model of the factory, and Friis represented the manufacturing context.

Paper 3 **Bärring, M.**, Shao, G., Helu, M., & Johansson, B. (2020). A Case Study for Modeling Machine Tool Systems Using Standard Representations. *2020 ITU Kaleidoscope: Industry-Driven Digital Transformation (ITU K)*, 2020, 1-8. doi: 10.23919/ITUK50268.2020.9303218

Contribution Bärring was first author of the paper and performed the development work of the use case presented in the paper with support of Shao. The idea to the study and the writing of the paper was done in close collaboration with all co-authors (Shao, Helu, and Johansson).

Paper 4 **Bärring, M.**, Shao. G., & Johansson, B. (2020). Digital Twin for Smart Manufacturing: the Practitioner's Perspective. *Proceedings of the ASME 2020 International Mechanical Engineering Congress and Exposition. Volume 2B: Advanced Manufacturing*. Virtual, Online. November 16–19, 2020. https://doi.org/10.1115/IMECE2020-24037

Contribution Bärring was first author developing the interview study together with Shao. Bärring performed the interview study with industry companies from Project B and transcribed the interviews. The analysis of interview responses plus writing and editing was done in collaboration with the co-authors (Shao and Johansson).

Paper 5 **Bärring, M.**, Shao, G., Hedberg, T. Jr., & Johansson, B. (2021). *Identifying Use Cases and Requirements for Digital Twins in Supply Chains from Research and Practice*. Submitted to journal.

Contribution Bärring was first author of the paper, coordinating the writing and development of the manuscript. Bärring was mainly responsible for writing the first parts of the paper, Shao for the standards landscape, and Hedberg for defining use cases and requirements for digital twins in supply chains. The entire manuscript was developed in close collaboration with all co-authors (Shao, Hedberg, and Johansson).

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

3D	Three dimensions
5GEM	5G Enabled Manufacturing
AP	Application Protocol
API	Application Programmable Interface
CNC	Computer Numerical Control
CSI-lab	Chalmers Smart Industry Laboratory
CPS	Cyber-Physical Systems
CPPS	Cyber-Physical Production Systems
DIN	Deutsches Institut für Normung
EDI	Electronic Data Interchange
ERP	Enterprise Resource Planning
IoT	Internet of Things
IIoT	Industrial Internet of Things
ICT	Information and Communication Technology
IDT	Information and Digital Technology
ISO	International Organization for Standardization
IT	Information Technology
JSDAI	Java-SDAI
JSON	JavaScript Object Notation
LiDAR	Light Detection and Ranging
MOST	Mobile Operator Support System
MQTT	Message Queuing Telemetry Transport
noSQL	not only Structured Query Language
OEM	Original Equipment Manufacturer
OPC UA	Open Platform Communications Unified Architecture
PLC	Programmable Logical Control
RAMI 4.0	Reference Architecture Model for Industrie 4.0
RPI	Raspberry Pi
SDAI	Standard Data Access Interface
SDO	Standard Development Organization

SIS	Swedish Institute for Standards
SM	Smart Manufacturing
SME	Small- and Medium-Sized Enterprise
STEP	STandard Product Exchange Protocol

LIST OF FIGURES

LIST OF TABLES

1

INTRODUCTION

This introduction presents a background to the research area and problem. It explains the vision for future manufacturing organizations and the aim of this research. This leads on to the research questions, which provide support in realizing the aim and vision. Furthermore, this introduction defines the research stakeholders and delimitations, plus the structure of this thesis.

1.1 BACKGROUND

The digital transformation is changing the nature of work in most industries. Indeed, from a connectivity perspective, anything that gains value from a connection is expected to have a connection in the future (Ericsson, 2017; Ericsson, 2011). Business activities that can be digitalized via ever-cheaper digital technologies will create new sources of information. These new sources will provide more process measurements, thus contributing to what may be known about businesses (McAfee and Brynjolfsson, 2012). Processes, equipment, and humans in a manufacturing system generate large volumes of data, and many companies entering today's global market, are, more or less, born digital. They collect as much data as they can and ground their decision-making in what the data reveals (Mayer-Schönberger and Cukier, 2013).

1.2 RESEARCH PROBLEM

The manufacturing field is currently undergoing a Fourth Industrial Revolution, with digital technologies providing new opportunities for connecting and collecting data from production equipment. Despite these new opportunities, manufacturing organizations are still lagging behind organizations that are born digital. Why has this sector neither learned from the digital companies and not embraced the digital technologies yet?

The reason manufacturing organizations are not already digital-driven is down to obstacles encountered when implementing digital technologies. These obstacles relate to both organizational and technical aspects. On the organizational side, there is a challenge in understanding how data may support decision-making in manufacturing organizations. On the technical side, the obstacles, include how digital technologies integrate data flows, support the sharing of data, and enable interoperability between various information systems.

1.3 VISION

My vision is for future manufacturing organizations to be driven by fact-based decision support based on data rather than of relying mainly on intuition and experience.

1.4 AIM

The aim of this thesis is to show manufacturing organizations the applicability of digital technologies in digitalizing manufacturing system data to support decision-making and how data sharing may be achieved.

1.5 RESEARCH QUESTIONS

To achieve the aim of this thesis and contributing to the vision of future manufacturing organizations being driven by fact-based decision support, two research questions have been drawn up.

> ***RQ1)*** *How do manufacturing system lifecycle decisions influence the requirements of data collection towards interoperability?*

The first question addresses the requirements of data, depending on which decision it refers to in a manufacturing system lifecycle. The manufacturing system lifecycles investigated here are design, operations, and maintenance. These were chosen because they are all important to a manufacturing system's performance.

> ***RQ2)*** *What makes interoperability standardization applicable to sharing data in a manufacturing system's lifecycle?*

The second question relates to how data may be shared, once it has been collected and analyzed. One of the current issues in manufacturing is that data and information are isolated in silos and not shared between organizations, or even between functions within the same organization. Interoperability standards exist but are not applied as much as they could be. Therefore, the second question investigates what makes interoperability standards applicable in supporting data-sharing in a manufacturing system's lifecycle.

1.6 DELIMITATIONS

The variables in this research are: 1) the type of manufacturing system lifecycle decision, 2) the digital technologies for enabling data to provide decision support, and 3) the data needed for decision support. The research presents the decision that should be supported by data. However, the actual decision-making process is not studied. Moreover, no one digital technology is the only solution available. Rather, they serve as examples of how more data on a manufacturing system may be enabled. The applicability and extension of the use of standards are studied, but not the standardization process itself.

1.7 STAKEHOLDERS

The manufacturing industry has a significant impact on society and plays a big role in productivity gains of a nation, the creation of jobs, and impact on the environment and climate, etc. To keep competitiveness in a country like Sweden, we need to understand how the digital transformation in manufacturing should be approached with required changes in processes and competencies. The digital transformation involves both benefits and challenges and this research is therefore relevant to a number of stakeholders that are crucial for the direction of the digital transformation. Stakeholders to this research include:

- *Manufacturing organizations:* the research is targeted to support manufacturing companies and the aim is to demonstrate to manufacturing companies how they can apply the new technologies to make more fact-based decision-making. Beyond the manufacturing organization, production personnel and decision-makers in manufacturing organizations are also important stakeholders since the results suggest how their work will change.
- *Standardization bodies:* to make standards applicable and serve the needs of manufacturing, an interaction between research and standardization is important. This research will address the applicability of standards in manufacturing and how they can be made more applicable.
- *Politicians and funding agencies:* the digital transformation is happening now and in order to strengthen the competitiveness of Swedish industry in a global market, a joint collaboration between industry, academia, and the government is needed. Funding to establish this collaboration is crucial to be able to make joint efforts and create a neutral platform for collaboration. An additional aspect is an infrastructure that will be needed in the digital transformation. These are aspects that politicians and funding agencies can impact on and this research is relevant for demonstrating pieces that are needed for making the transition.
- *Academia:* the results of this research contribute with both proofs-of-concept of how the new digital technologies can be applied to solve manufacturing problems and with statements from practitioners in manufacturing of how they view possible benefits and challenges of the new technologies. By applying a mixed methods research, the results can provide both quantitative and qualitative results to answer how manufacturing organizations should reach the vision of this thesis.

1.8 STRUCTURE OF THESIS

The remainder of the thesis is structured as seven chapters, covering the following topics: frame of reference, research approach, results, answering research questions, discussion, and conclusions. The content of each chapter is:

2 **Frame of Reference**
Introduces the relevant concepts for the thesis including manufacturing systems and paradigms, definition of data, information, and knowledge, and digital technologies and interoperability standards.

3 **Research Approach**
The chapter explains the methods used in collecting the data presented in the results and how these methods were selected to support answering the RQs. Papers, projects, and studies are presented and explained.

4 **Results**
Presents the results from studies in connected factory, standard representation of machine model data, and digital twin for smart manufacturing. Results are included from appended papers which helped to support RQs.

5 **Answering Research Questions**
The two research questions are answered based on the results presented in *Results*.

6 **Discussion**
This chapter connects theory and results in the areas of: manufacturing system lifecycle; data and interoperability; vision for future manufacturing system; quality of research; and stakeholders and sustainability.

7 **Conclusions**
This chapter presents the thesis' concluding remarks.

Appended Papers 1-5

2

FRAME OF REFERENCE

The frame of reference will introduce the concepts and theoretical background to this research. Firstly, a model introduces the idea behind this thesis and show how the different concepts relate to each other moving from reality to decision support based on data that describes the reality, Figure 1. This model was previously introduced in the author's Licentiate thesis (Bärring, 2019). It will serve the same purpose in this thesis; linking concepts to the idea of more data-driven decision-making. The various concepts are then introduced. These include manufacturing and production system, current trends and manufacturing paradigms (Industry 4.0, Smart Manufacturing Systems, and Cyber-Physical Systems), the definition of digital technologies, the distinction between data, information, and knowledge, and lastly standards and interoperability standards.

2.1 MOVING FROM REALITY TO DECISION SUPPORT

The research in this thesis focuses on how data may be made available to support decision-making in manufacturing and how it may be shared throughout the different lifecycle stages of manufacturing. Figure 1 visualizes the concept behind this research using reality, data, and decision support. The reality aspect entails a production system involving equipment, processes, and humans. Data is the digital depiction representing the behavior and condition of reality; in this case, a production system. Decision support is based on data making it possible to act on what is happening in reality. The lower part of Figure 1 also visualizes what happens between reality, data, and decision support. The steps in between explain how data are collected, managed, stored, and communicated. This will be explained more in-depth in the subsequent sections.

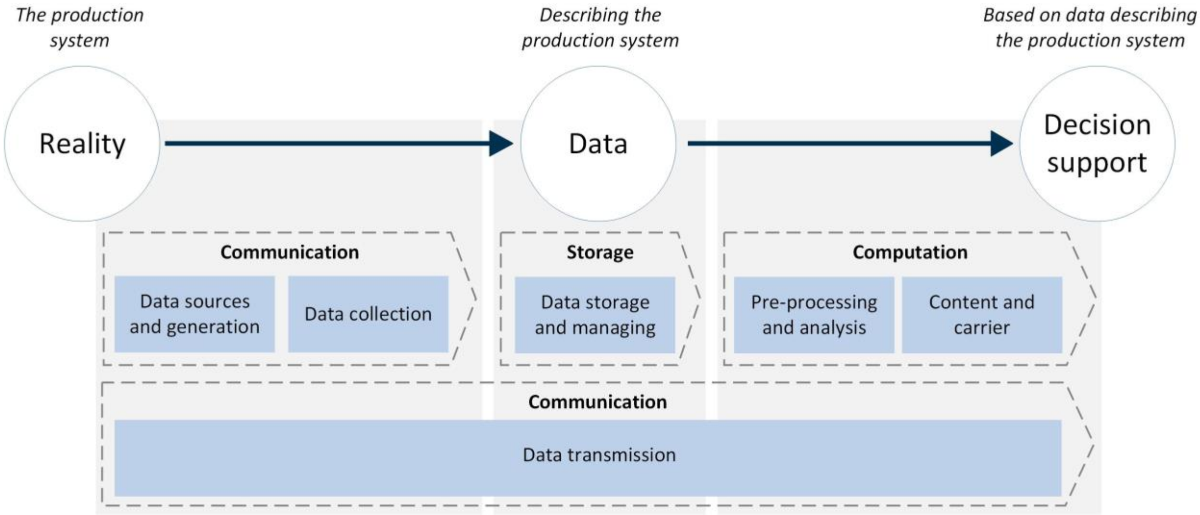

Figure 1. Summarizing and connecting the concepts that are used in the thesis (Bärring, 2019)

2.2 MANUFACTURING SYSTEMS

Producing is a transformation of input to output (Wu, 1994). It is the process of combining material, resources, labor, and capital to create products and/or services (CIRP, 1990; Jonsson and Mattsson, 2009). Transforming from input to output requires technology, humans, energy, and information. These also need to be organized and managed effectively to support the transformation of material to its finale state, involving a sequence of value-adding activities and operations (Bellgran and Säfsten, 2010; Jonsson and Mattsson, 2009). A production system constitutes sub-parts that make the transformation possible. Each sub-part has relationships to other sub-parts and orchestrating these requires a holistic perspective on the production system. A holistic perspective is also used in designing a production system. This includes all sub-parts, bearing in mind both technical and physical aspects (Bennet, 1986). Facilities, humans, and equipment (e.g., machines), software, and procedures. An overview of the transformation process is shown in Figure 2.

"Production" and "manufacturing" are terms often used in the same context to explain the transformation of products. However, the should not be viewed as interchangeable, because they are distinct. Manufacturing production (or just "production") is the definition of the physical acts and processes that transform material into a final product. By definition, manufacturing also includes the physical act of transforming the material into a product. However, it goes beyond this. A manufacturing system also incorporates the interrelated activities for realizing a product and getting it out to market. These activities include the design, selection, planning, production, quality assurance, management, and marketing of products. The term "manufacturing" is more or less a summary of all the activities needed to realize a product (Hounshell, 1984; CIRP, 1990). Section 2.2.1 *Manufacturing System Lifecycle*, will explain the lifecycles of a manufacturing system.

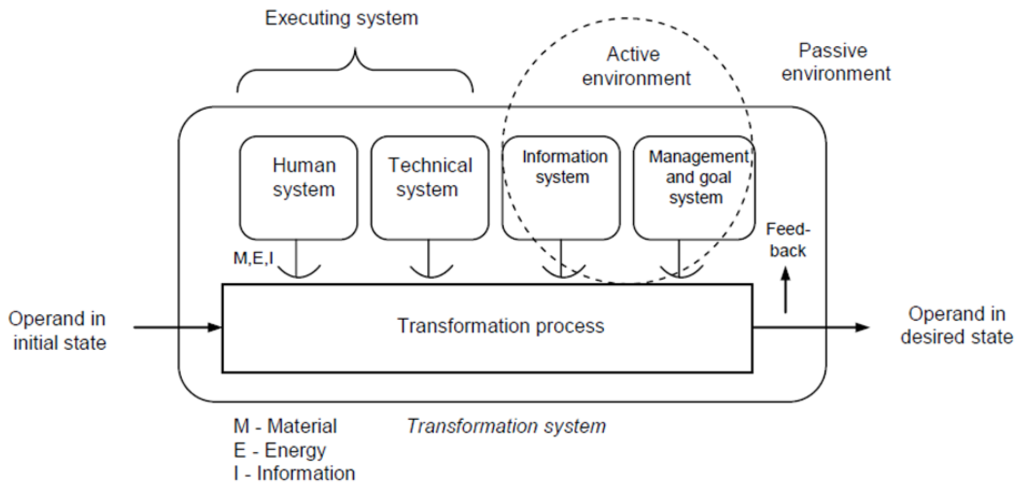

Figure 2. Overview of the transformation process in a production system (Hubka and Eder, 1988)

2.2.1 Manufacturing System Lifecycle

Production is about the transformation of input to output and the activities within a production system are often communicated based on its product lifecycle. These activities are divided into the areas of the market, engineering, production, distribution, service, and recycling. *Market activities* set the requirements for the expected output in terms of quality and productivity, etc. *Engineering activities* involve product development and supply the prerequisites for production. *Production activities* create the product. *Distribution activities* ensure delivery of the product to a customer as specified. *Service activities* do occur during a product's life; these are aimed at preventing and removing any product defects that may appear. When a product wears out is the point at which *recycling activities* begin. These are aimed at saving resources and handling used material (Bellgran and Säfsten, 2010).

Besides viewing production system activities and operations solely from the perspective of the product, a production system may also be considered on the basis of its lifecycle. Like a product, a production system includes activities surrounding the planning and design of a production system, until it is phased out at the end of its life. More stringent reuse requirements are relevant, not only to products but also production system. Production systems should, therefore, be planned and designed to serve the needs of several product generations. Today's production systems follow a parallel development rather than the traditional sequential one, normally with continual change taking place, see Figure 3. As the figure shows, a new production system may be designed and realized in parallel while the existing production system is still in operation. The nature of a production system changes during its lifecycle phases, as do the requirements of its capabilities. It is essential to know the current lifecycle position of a production system to evaluate the placement of requirements (Bellgran and Säfsten, 2010).

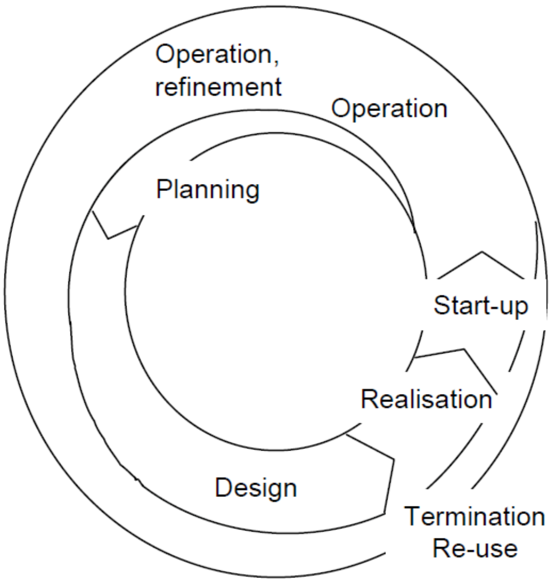

Figure 3. The lifecycle of a production system (Wiktorsson, 2000)

This thesis will focus on manufacturing systems lifecycles **design, operations, and maintenance**. Thus, to provide common ground for the remainder of the thesis, these phases will be further explained. The word **"design"** relates both to the object being designed and the action of doing the design work. The design of a production system is the action and the work of deciding what the system should look like, including the physical and organizational solutions. Design something involves change and that change may be either an improvement to an existing system or a development of an entirely new one. The degree of change may be distinguished by examining modification, improvement, and design (Bellgran and Säfsten, 2010). In comparing improvement and design, improvement is the action of moving a production system closer to a standard or norm, but design is a creative process that should question existing solutions in a system (van Gigch, 1991). Design is iterative, as indicated in Figure 3. Ideally, making a design should result in a decision favoring a design that fulfills all the formulated requirements (Bellgran and Säfsten, 2010).

Operation is the phase of the manufacturing system in which the transformation of input to output takes place. For any company in a competitive environment, the overall goal is to achieve profit and gain a leading position resulting in business success. For a production system to contribute to business success, it is crucial to understand the performance of a production system and its ability to fulfill defined requirements. Measures commonly used for determining performance are productivity and efficiency. *Productivity* is an absolute measure of what is produced relative to the efforts required to achieve this. It is also expressed as output related to input at a given point in time (Bellgran and Säfsten, 2010). *Efficiency* describes the ability to do things right and *effectiveness* is doing the right things (Olhager, 2000; Hill, 2000; Neely, Gregory, and Platts, 1995). Relating effectiveness and efficiency to productivity, effectiveness is associated with output and efficiency with input. Sink, Tuttle, and Shin (1989) define some important production measures:

- ***Efficiency:*** doing things right.
- ***Effectiveness:*** doing the right things.
- ***Quality:*** a measure that is important to the entire value chain and may be described by quality checkpoints.
- ***Good working environment:*** covers how personnel in a production system perceive various aspects, for example, the wages system, task identification, culture, leadership, etc.
- ***Innovation:*** the creative ability.
- ***Profitability:*** the relationship between revenues and costs.

During operations in a production system, there is a risk of disturbances interrupting production. Running a production system involves dealing with the challenge of avoiding these disturbances or, if they cannot be avoided, being able to handle them. Being able to handle this means creating a robust, reliable system. Reliability means identifying the causes of failures and trying to eliminate them plus identifying the consequences of failures. This reduces and eliminates their effects and thereby increases the tolerance of failures. Reliability impacts the availability of a production system and is associated with maintainability and maintenance support. The **maintenance** of a production system encompasses activities affecting a unit's functional ability to uphold production during operation, or bring it back to the previous level when disruptions occur (Bellgran and Säftsen, 2010). Activities include technical, administrative, and managerial actions to maintain or restore a unit to its original state in which required functions can be performed during its lifecycle (CEN, 2001; EN, 2010). The definition of maintenance includes the two most important categories of maintenance, i.e., preventive and reactive (or corrective) maintenance. Preventive maintenance is done prior to a failure and aims to keep a system at its operational level. Reactive maintenance takes place when a failure has occurred and is intended to restore (EN, 2010). More generally, production maintenance includes procedures that make a production system work (Bokrantz, 2019), and is a crucial support process in ensuring the well-being of a production system (Holweg et al., 2018).

2.3 DIGITAL TECHNOLOGIES

Digital technologies have had an immense effect on how our society functions, stimulating economic growth and increased productivity. Digital technologies include computers, robots, cell phones, and digital watches; their common denominator is the integrated computer chip that controls and runs them (Cortada, 2004). The introduction of devices for digital measuring and storage made the process of datafying more efficient. It also made mathematical analysis to uncover the hidden value in data easier (Mayer-Schönberger and Cuiker, 2013). The second half of the Twentieth Century saw computers brought into the manufacturing domain. This impacted how products were manufactured and distributed in supply chains. Now, computers are becoming an integral part of all aspects of manufacturing (Cortada, 2004). In terms of, the Industry 4.0 Maturity Index method, computerization is the first step towards Industry 4.0 (also termed as Industry 3.0) (Schuh et al., 2017).

Digital technologies are a basis for information technologies (IT). What has been seen in the development of digital technologies is that they have become more powerful in handling and storing large amounts of data and quicker at performing functions. This development has taken place at the same time as digital technologies have become cheaper and more affordable. One visible change is a decrease in size and weight, but digital technologies and devices have also become more reliable and able to handle more data and complicated instructions (Cortada, 2004). In parallel with the development of hardware was an increased trend toward IT infrastructure and services provided through smart networks (cloud computing). Devices are connected with each other and to the Internet by wireless networks, thus connecting the virtual and physical world, i.e., Cyber-Physical Systems (CPS) (Kagermann et al., 2013).

To define digital technologies, Hilbert and López (2011) divided both analog and digital technologies into the functionalities of communication, computation, and storage, see Figure 4 (an adapted version from Hilbert and López, 2011). Communication of information (or transmission through space), is information sent and received by a user over a considerable distance. Storage of information (or transmission through time), means maintaining information over time and being able to supply it to a user when requested. Computation involves the meaningful transformation and processing of information and may also be explained as the repeated transmission of information through time and space, guided by an algorithmic procedure (Hilbert and López, 2011).

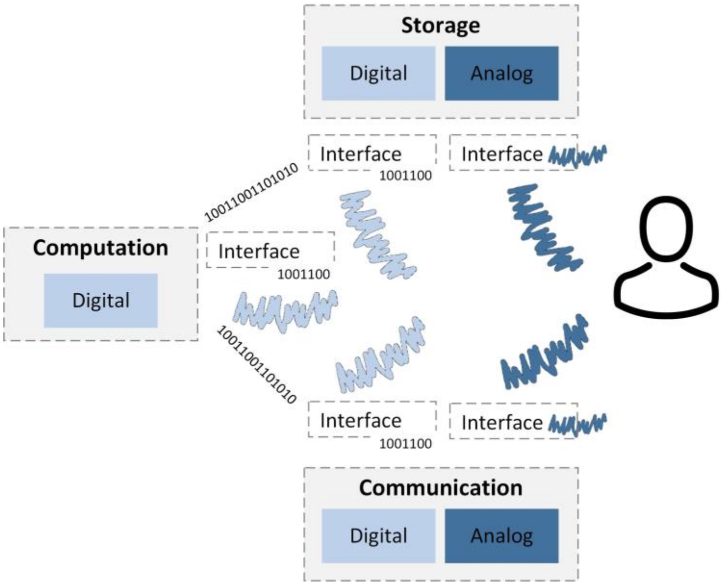

Figure 4. The three basic information operations (adapted from Hilbert and López, 2011).

Digitalization is defined as the use of computer and Internet technology to support a more efficient and effective economic value-creation process (Reddy and Reinartz, 2017). Besides changing business processes and company products, digitalization may also change the process of an entire supply chain. Digitalization is creating major changes and what is taking place now has been called a "digital transformation" (Horváth and Szabó, 2019). This digital transformation relies on Internet technologies and the connectivity they enable to deploy both traditional IT and emerging IT solutions (Ghobakhloo, 2018; Ghobakhloo, 2019). The various IT and digital technologies being used may be described collectively as information and digital Technologies (IDT). The current digital transformation is strongly linked to extensive use of IDT in creating business value (Ivanov, Dolgui, and Sokolov, 2019).

2.4 DATA, INFORMATION, AND KNOWLEDGE

2.4.1 Data and Information

"Data" refers to a quantifiable set of discrete, objective facts about an event that has taken place (Skoogh et al., 2012). It is also the raw material for creating information (Davenport and Prusak, 1998). The transformation from raw indicator to insight comes when the meaningful interpretation of data into information takes place and will support decision-making. Besides being the raw indicator of an event, other characteristics of data are that it may easily be copied, combined with other data, and be used by multiple users at the same time (Manyika et al., 2011). Data may also contain value even after its first use, since it may be used over and over again without wearing out. Even when the amount of value gained from the first use of a data set is low, the total value may be large if the data are exploited effectively (Mayer-Schönberger and Cuiker, 2013). As data are further processed by contextualizing, categorizing, calculating, or condensing a message containing information is created. The information contains data of purpose and relevance to a given context, and that impacts a receiver's understanding of something (Davenport and Prusak, 1998). This should decrease the actual uncertainty of the condition and, from an information theory perspective, information is defined as the opposite of uncertainty (Shannon, 1948).

Data models are used to describe data elements and their relationships with each other. A data model needs to be defined, to provide the relevant meaning of data elements in a given context. Interoperable data are data shared between at least two systems. Data may be shared either in batches or in real-time. The real-time sharing of data is often desirable, as it always provides always the latest data. However, processing data in batches does have the benefit of being easier to manage, check, filter, and rearrange offline before being shared with the end-user (Shepherd, 2006).

2.4.2 Big Data

In industry and society, the amount of data available has increased tremendously in recent years. It is also increasingly viewed as a valuable asset that needs to be correctly exploited, as organizations take more care of their data now. Big data is used to explain this change and is characterized by massive unstructured datasets that also need to be handled and acted upon in timely fashion. From a technical standpoint, big data is data that cannot be perceived, acquired, managed, or processed by traditional IT solutions and software/hardware within an acceptable time frame (Chen, Mao, and Liu, 2014). The first known reference defining big data is from a Gartner report published in 2001, where big data is defined as the volume, velocity, and variety of data (the three Vs of data) (Laney, 2001). Volume implies the amount of data being created and handled the velocity is the speed that data should be retrieved, analyzed, and acted upon; and variety is the numerous data sources of data including unstructured and heterogeneous data. Data may now be retrieved in the form of messages, updates, images, readings from sensors, and locations from cell phones (McAfee and Brynjolfsson, 2012; Gandomi and Haider, 2015; Koscielniak and Puto, 2015). Table 1 summarizes the steps that need to be taken when going from reality to data and in creating a data value chain. There are four main steps: the generation, acquisition, storage, and analysis of data (Chen, Mao, and Liu, 2014).

Table 1. The data value chain with an explanation of the steps for handling Big Data (adapted from Chen, Mao, and Liu, 2014)

<table>
<tr><th colspan="2">Data value chain steps</th><th>Definition</th></tr>
<tr><td colspan="2">Data</td><td>Raw material</td></tr>
<tr><td colspan="2">Data generation</td><td>Data sources generating data include sensors, videos, clickstreams, and/or all other available data sources.
It is data about operation and trading information in enterprises, logistic and sensing IoT data, the interaction between humans and positioning.</td></tr>
<tr><td rowspan="3">Data acquisition</td><td>Data collection</td><td>Data collection is the process of applying a data collection technique for acquiring raw data from a selected data generation environment.</td></tr>
<tr><td>Data transmission</td><td>As data have been collected, data is transported to a data storage infrastructure where it should be pre-processed and analyzed in a later stage.</td></tr>
<tr><td>Data Pre-processing</td><td>Data collected from numerous sources vary with respect to noise, redundancy, and consistency, etc. To avoid storing and managing data not meeting the quality requirements, a pre-processing step takes place before the analysis of data. To go through this step can both save many and time, but also improve the accuracy of the analysis in a later stage.</td></tr>
<tr><td colspan="2">Data storage</td><td>Storage and management process of data that also should ensure the reliability and availability to access the data. The infrastructure should both care for reliable storage space and powerful access for querying and analyzing data.</td></tr>
<tr><td colspan="2">Data analysis</td><td>A production process that utilizes the raw material to create new value. By analysis and transformation of the raw material to information, meaningful insights and values can be provided.</td></tr>
</table>

2.4.3 Decision Support

Making a decision happen in situations where a selection must be made or the situation will remain unsolved. Making an informed decision in these situations is where data can provide support. Thus, data is also a tool whereby decision-makers may support decision-making. As stated, information is the meaningful interpretation of data and information can restructure, add to, or change the information receiver's knowledge. Information is thereby the flow of messages that can create and organize a receiver's knowledge (Machlup, 1983). Collecting and turning data into information involves contributing to knowledge. To explain how data and information relate to each other, Figure 5 presents the data, information, knowledge, and wisdom hierarchy. Data is at the bottom and wisdom at the top, with information and knowledge as intermediate steps that must be fulfilled. The hierarchy visualizes how data are used to create information, contribute to knowledge, and may ultimately provide wisdom. Another way to explain this is that turning data into information involves "understanding relationships," turning information into knowledge involved "understanding patterns," and turning knowledge to wisdom involves "understanding principles" (Bellinger, Castro, and Mills, 2004).

Figure 5. The data, information, knowledge, and wisdom pyramid (Rowley, 2007)

2.5 MANUFACTURING PARADIGMS

Manufacturing is undergoing a Fourth Industrial Revolution succeeding mechanization through water and steam, mass production with assembly lines, and the automation era that applied information and automation technologies to manufacturing. Manufacturing paradigms that influence the Fourth Industrial Revolution and will be discussed here are Industry 4.0, Smart Manufacturing Systems (SMS), and Cyber-Physical Systems (CPS). They all involve a transition to a more data-heavy focus, supply network-wide integration of information and communication technology (ICT), and increased automation with humans still involved in the system (Thoben, Wiesner, and Wuest, 2017).

ICT was also used in manufacturing prior to the Fourth Industrial Revolution. In Supply Chain Management (SCM), ICT was introduced as early as in the 1960s with the integration of Electronic Data Interchange (EDI). The ICT tools Material Requirements Planning (MRP) in the 1970s and Manufacturing Resource Planning (MRP II) in the 1980s soon followed EDI, and in the 1990s Enterprise Resource Planning (ERP) became an integral part of the business (Lavassani, Movahedi, and Kumar 2008; Alfalla-Luque and Medina-Lopez, 2009). These and other ICT tools have been developed and adopted to support supply chains that are increasingly complex to manage (Jacobs 2007; Lavassani, Movahedi, and Kumar, 2008).

The Internet of Things (IoT) or Industrial IoT (IIoT) involves standard technologies that connect devices and populate them with embedded computing capabilities. The concept revolves around connecting “things” to each other and the Internet. In a manufacturing setting ”things” means materials, sensors, actuators, controllers, robots, human operators, machines, production and material handling equipment, and products. Connecting devices and products, i.e., “things”, enables them to communicate and interact with each other. The technological aspects of IoT, that enable communication and interaction between “things,” facilitates responses in real-time, decentralized analysis, and data-based decision-making (Yang et al., 2019; Rüßmann et al., 2015). These functionalities support the identification of machine errors and trends in production lines, plus finding optimal parameters for maximizing the quality of products while decreasing wasteful parameters. IoT/IIoT should be seen as enablers of SM and Industry 4.0 and may thus provide more flexibility, agility, and innovation.

2.5.1 Industry 4.0

Industry 4.0 was a German initiative for strengthening the competitiveness of the German manufacturing sector in times of digitalization. The term itself, Industry 4.0, was first introduced at the Hannover Messe ("Hanover Fair") in 2011 and since the publication of "Industrie 4.0 Working Group" in 2013, Industry 4.0 has been viewed as a technological framework (Kagermann et al., 2013). The Industry 4.0 technological framework includes a wide variety of technologies, principles, and methods to support more autonomous, dynamic, flexible, and precise production systems and supply chains (Tortorella and Fettermann, 2018). As a paradigm, Industry 4.0 also addresses how ICT may be used in an industrial context and advocates the use of data to support decision-making at every level in a business (Schuh et al., 2017). Data sources in production systems are from production equipment and production-related information systems, plus enterprise and customer management systems (Rüßmann et al., 2015). Like SMS, Industry 4.0 relies on technological advancement and supports integration, automation, and optimization of production flows that previously existed in isolated silos. The enabling technologies include (Yoon, Shin, and Suh, 2012):

1) a horizontal integration that can provide an information highway for seamless sharing of information from the product lifecycle to connected stakeholders;

2) vertical integration for handling sensors, devices, and communication collecting data from the product and production process in the real production system, and;

3) a system engineering technology for creating ubiquitous systems, including vertical and horizontal integration.

In Industry 4.0, IDT refers to the application of enabling technologies that support digital transition beyond organizational boundaries, including the creation of intelligent supply chains and connected customers (Gilchrist, 2016; Ghobakhloo, 2018). Relative to the term "digitalization", Industry 4.0 may be viewed as a sub-concept (with digitalization the over-arching concept) (Horváth and Szabó, 2019). Industry 4.0 production systems and supply chains are distinguished by the presence of highly automated, digitized processes (Lu, 2017). IDT in Industry 4.0 allows integrated processes at the intra- and inter-organizational levels to provide a set of solutions for informatization and automatization of processes in which machines can interact with each other (Ghobakhloo, 2018; Ghobakhloo, 2019; Xu, Xu, and Li, 2018; Ivanov et al. 2016; Strozzi et al., 2017). In Industry 4.0, IDT includes (Gilchrist, 2016; Lu, 2017; Ghobakhloo, 2019):

- the application of e-commerce tools such as EDI;
- the adoption of Advanced Manufacturing Technologies (AMT) such as Computer Aided Design (CAD), Computer Aided Manufacturing (CAM), Computer Aided Engineering (CAE), Industrial Simulation, and ERP, and;
- the most advanced IDT including the Internet of Things (IoT), Augmented Reality (AR), Additive Manufacturing, Blockchain, Cloud Computing, and Big-Data analytics.

Industry 4.0 is closely associated with the Reference Architecture Model for Industrie 4.0, abbreviated to **RAMI 4.0**. This is a reference model for an Industry 4.0 reference architecture and provides a structured description of the fundamental ideas relating to Industry 4.0 (DIN, 2016). The term "asset" is central to RAMI 4.0. An asset has its application in the physical world, or, it may be an information carrier. However, it may be both; something known as an "intelligent field device." Assets in the physical world carry information and must be integrated in the technological information network to communicate. Figure 6 shows the RAMI 4.0 architecture model and is structured along three axes:

- the architecture axis (“Layers”), divided into six layers for representing information relevant to the role of the asset;
- the “Life cycle & value stream” axis, based on the IEC 62890 standard and representing the lifetime of an asset and the value-added process, and;
- the “Hierarchy levels” axis, assessing functional models to specific levels and based on the DIN EN 62264-1 and DIN EN 61512-1 standards.

Using its axes, RAMI 4.0 provides a structured description of the main elements relating to an asset. It also supports breaking down the complex interrelationships, to make things more manageable at each point in an asset’s life. RAMI 4.0’s aim is to describe, with sufficient precision, an asset and the combination of assets. Industry 4.0 components (or I4.0 components) consist of an asset and an administration shell. The administration shell converts an asset into an I4.0 component and is a virtual digital and active representation of an asset in an I4.0 system. It records the lifecycle data of an asset and may convert it into information.

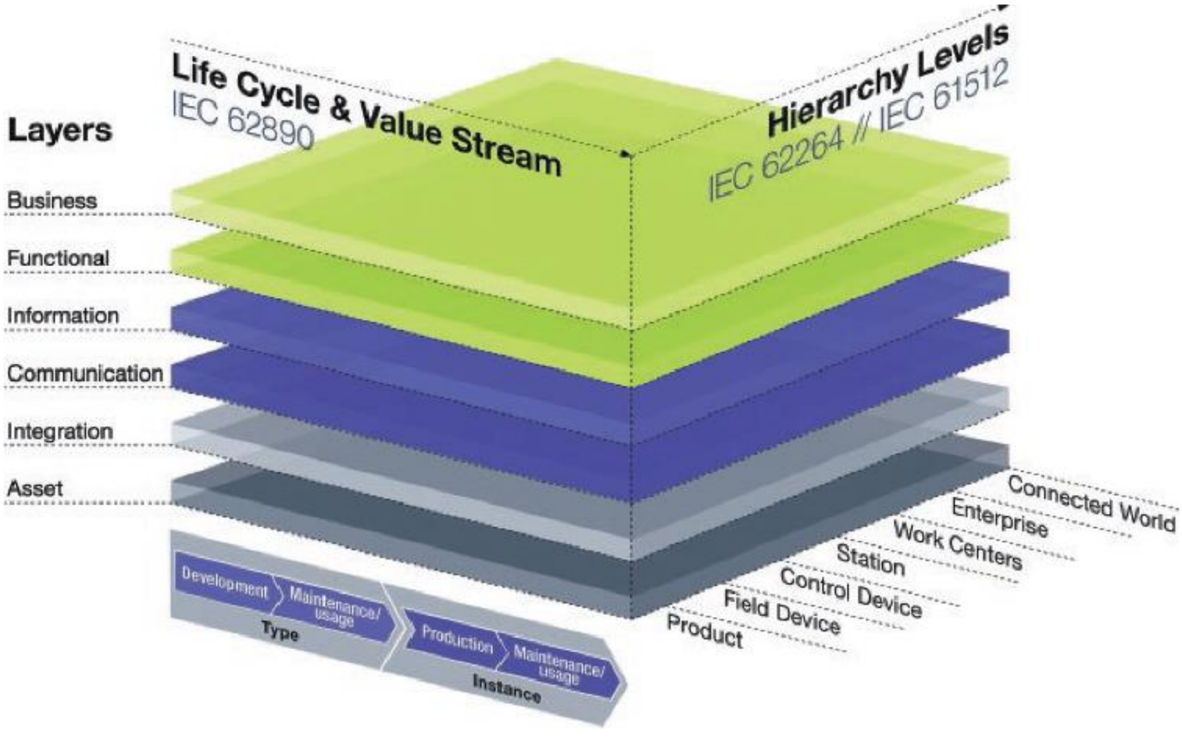

Figure 6. RAMI 4.0 Architecture with the axes Layers, Life Cycle & Value Stream, and Hierarchy Levels (DIN, 2016)

2.5.2 Smart Manufacturing Systems

Smart Manufacturing Systems, SMS, are production systems with rapid and widespread information flow supported by the new technologies. The more rapid sharing and flow of information will then also require a quick response to it in the manufacturing processes. Intelligent decision-making based on real-time data will be a decisive part of SMS to adapt to new situations in an agile manner (Davis et al., 2012). The realization of SMS depends on a combination of functionalities from prior manufacturing paradigms and the emergent advancements in ICT. Different from other technology-based manufacturing paradigms, smart manufacturing defines a vision for the next generation of manufacturing that has enhanced capabilities. It relies on earlier manufacturing paradigms but is also built on ICT emerging now (Lu, Morris, and Frechette, 2016). The characteristics of SMS are (Kusiak, 2017):

1) every part of a manufacturing enterprise is digitized;
2) the system's intelligence is distributed to achieve real-time control and a high degree of flexibility;
3) management of supply chains is collaborative and response to market is fast;
4) decisions related to energy and resource efficiency are integrated and optimal, and;
5) a product's innovation cycle is fast. SM is not only about automating production systems, but also autonomy, evolution, simulation, and optimization.

Lu, Morris, and Frechette (2016) presented a *Smart Manufacturing Ecosystem*, see Figure 7, encompassing the three dimensions of product, production systems, and enterprise (business systems). The *product* lifecycle dimension includes information flows and control, from a product's design to its end-of-life. *Production* focuses on the design, deployment, operation, and decommissioning of a production system and its systems. *Business* includes the functions of supplier and customer interactions. All these lifecycles are related to the vertical integration in the *manufacturing pyramid* (middle of Figure 7), integrating machines, plants, and enterprise systems. Integrating all manufacturing software applications along the three dimensions supports advanced control at shop-floor level and makes optimal decisions at the plant and enterprise levels. The three dimensions have previously been handled in silos but, even in just one of these dimensions, integrating is a complicated endeavor. SMS still needs a high-level reference architecture. It includes functional models and architectural definitions to integrate functions within and across the enterprise including between suppliers and customers. This will create opportunities for dynamic production capabilities and customized products. An SMS vision is for products that can contain all the relevant information relating to the history of how, when, and where they were manufactured. Realizing SMS and gaining the full potential of its capabilities means replacing classic manufacturing systems with an architectural paradigm based on a hierarchical control. The new manufacturing paradigm needs to be based on a distributed manufacturing service. This is realized by introducing smart devices that are accessible as services on a network, with embedded intelligence at every level, predictive analytics, and cloud computing technology. The development of smart manufacturing standards will play a key role since standards allow a manufacturing system to be systematic, repeatable, and efficient (Lu, Morris, and Frechette, 2016).

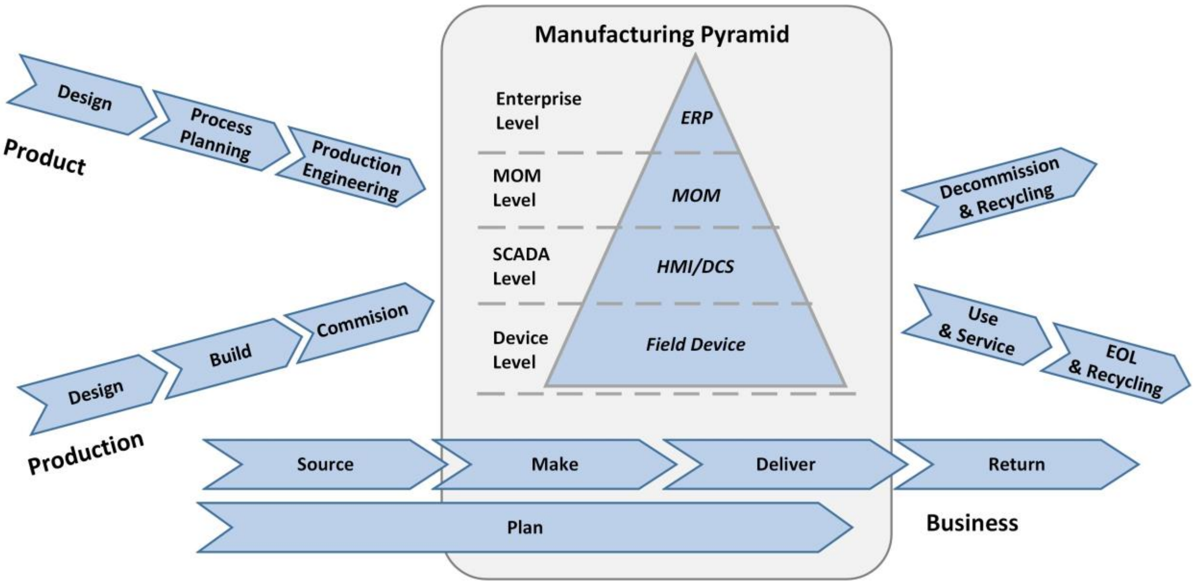

Figure 7. The Smart Manufacturing Ecosystem with axes Product, Business, and Production (adapted from Lu, Morris, and Frechette, 2016)

2.5.3 Cyber-Physical Systems

Cyber-Physical Systems (CPS) are systems that contain collaborating computational entities in close connection with the physical world. The system's ongoing processes concurrently provide and use data-accessing and data-processing services available through the Internet (acatech, 2011; Geisberger and Broy, 2012; NIST, 2013). CPS is also relevant to the production domain, where it is known as Cyber-Physical Production Systems (CPPS). This involves the newest foreseeable developments in the areas of computer science, ICT, and manufacturing science and technology. It will be an important part in realizing the Fourth Industrial Revolution, or Industry 4.0. The real and virtual worlds are growing ever closer together, driven by the Internet and forming the Internet of Things (IoT) (Kagermann et al., 2013).

CPPS consists of autonomous and cooperative elements, plus sub-systems that, depending on the situation, may be connected. This connection is on, and across all levels of production, ranging from machines and up to the production and logistics networks. As Figure 8 indicates, CPPS will break with a traditional automation pyramid in integration and information flows. The control and field levels still exist in future production systems, but at higher levels of the automation pyramid, with the connections and information flows becoming more decentralized in CPPS (Monostori, 2014). CPPS will transform the smart manufacturing ecosystem into a fully connected and integrated system, as shown in the right-hand part of Figure 8. Besides time- and safety-critical manufacturing functions at shop-floor level, all manufacturing functions along the three dimensions and in the manufacturing paradigm become virtualized and hosted as services (Lu, Morris, and Frechette, 2016).

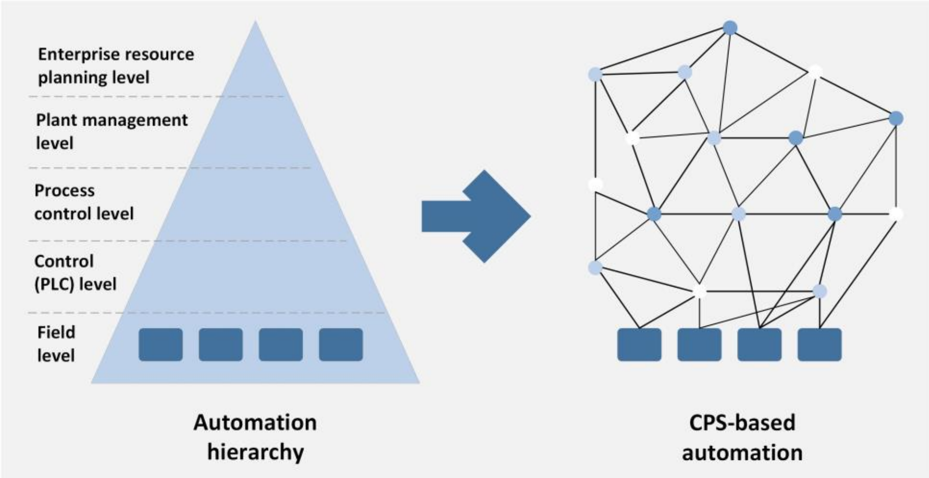

Figure 8. Automation hierarchy transforming to decentralized CPS-based automation (adapted from VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik (GMA), 2013)

2.5.4 Vertical and Horizontal Integration

To enable interoperability between various IT systems and exchange data in production systems, consideration must be given to horizontal and vertical integration. The three necessary integration features for Industry 4.0 are (Kagermann et al., 2013):

- *horizontal integration:* integration of various IT systems used internally in the different stages of manufacturing, and in business planning processes and between companies in value networks;
- *vertical integration:* integration of IT systems used at different hierarchical levels in a production system, according to the ISA 95 automation pyramid. This goes from sensors and actuators to corporate planning levels to supporting an end-to-end solution;
- *end-to-end digital integration:* integration through the engineering process, allowing the digital and real-worlds to be integrated across a product's entire value chain. This spans a single company while also serving serves the customer requirements.

In a production system's hierarchical structure, vertical integration supports the integration of the various IT systems used at different levels within a production system. For vertical integration, the factory environment is the setting and the purpose is to make more data interoperable and accessible between the various systems used to handle data. To achieve vertical integration, the key is end-to-end digital integration of actuator and sensor signals through the various hierarchical levels to the ERP level. Horizontal integration focuses on the various IT systems used at the different stages of the manufacturing and business planning processes. This involves the exchange of materials, energy, and information. The setting may be within a single company and also in a value network involving numerous companies. The goal of the integration is to be able to deliver an end-to-end solution (Kagermann et al., 2013).

The International Society of Automation (ISA) 95 hierarchy, the automation pyramid, defines where a physical entity is situated in the production system's hierarchy. There are five levels, where Level 0 includes the physical process in production, Level 1 is the sensing and manipulation of production processes, Level 2 is monitoring and controlling, Level 3 is management of manufacturing operations, and Level 4 business planning and logistics. Placing these various levels in relation to response times, Level 2 operations may involve hours, minutes, or even seconds, while Level 4 might be months, weeks, or days (ANSI/ISA, 2005). ISA 95 is a reference model commonly used in developing automated interfaces between enterprise and control systems. The ISA 95 standard was developed to support global manufacturers in most industries with batch, discrete, and continuous processes (Lu, Morris, and Frechette, 2016).

2.5.5 Digital Thread

The manufacturing paradigms explained in section *2.5.1-3* rely on a digital thread to connect data and processes for smart products and production, and to create integrated ecosystems (Margaria and Schieweck, 2019). The term "digital thread" was coined, in context of the digital revolution of manufacturing complex products, to describe the required data flows between engineering, manufacturing and business processes, and across supply chains (Feeney, Frechette, and Srinivasan, 2015). Digital threads have a particular relationship to digital twins, as they connect real things with their virtual twin versions. Beyond this, a digital thread also connects communication networks, decision algorithms, and visualization necessary for the design phase, construction, and operation. It provides the holistic view and traceability of an asset throughout its entire lifecycle via an information-relay framework. This framework includes data, behaviors, models, protocols, security, and the standards relating to the asset and the context in which it should operate (Margaria and Schieweck, 2019; Gould, 2018). The digital thread also links disparate systems throughout the product lifecycle and supply chain (Hedberg et al., 2017). By linking disparate systems the collection, transmission, and sharing of data and information between systems may be achieved quickly, reliably, and safely. This will drive the use of data-driven applications to support the generation of domain-specific knowledge that underpins decision-making. It will also support requirement management and improved diagnosis, prognosis, and control of the design and manufacturing process (Helu, Hedberg, and Feeney, 2017).

2.6 STANDARDS AND INTEROPERABILITY STANDARDS

2.6.1 Standards

At their core, standards are a common language for exchanging information and supporting collaboration with other organizations and businesses occupying the same information space. Doing things in the same way as others within the same information space helps get things done (Harris, 2001). Standards and guidelines are commonly viewed as synonymous or similar to each other. However, standards have a greater weight of certainty and provide a method for evaluating compliance. When a standard is created, it goes through a formalized voting and commenting procedure by all those actors that might be affected or have an interest in its development (Carter, 1992). The importance of standards has been widely recognized when it concerns the creation of tools, content, and management systems intended to work together.

Many of today's devices are based on standards developed decades ago. Standards evolve alongside the technology it regulate. They safeguard investment in digital content for producers and as well as consumers. This is possible because a standard can support portability, hardware, and operating system independence and reusability (Shepherd, 2006). As standards mature and become widely adopted they can reduce the implementation burden, as developers and administrators do not need to understand the complexity of underlying protocols. Instead, they may focus on the core functionality of the product or service they are creating (Lewis et al., 2008). Information systems and software might be more functional, faster, and less expensive to design and maintain if there could be an agreed common way of packaging information (Harris, 2001). Getting diverse applications to share information requires agreement on the structure and function of the information to be shared (Lewis et al., 2008). There are seven criteria to test the success of a standard (Shepherd, 2006):

- *durability*. Will it stand the test of time?
- *scalability*. Can it grow from small to large?
- *affordability*. Is it affordable?
- *Interoperability*. Will one system work with another?
- *reusability*. Can it be reused within multiple contexts?
- *manageability*. Is it manageable?
- *accessibility*. Can we all use it?

In the manufacturing sector, existing standards are not sufficient for the service-oriented smart manufacturing ecosystem. For example, new standards are needed to support a reference architecture, cybersecurity, factory networking, supply chain integration, and data transfer from shop-floor to enterprise level (Lu, Morris, and Frechette, 2016).

2.6.2 Interoperability

Interoperability is defined by Brownsword et al. (2004) as the ability of communication entities to share specified information and be able to operate it, based on agreed operational semantics (Brownsword et al., 2004). Interoperability allows various solutions to work together, not just by deploying generic solutions but also by complementing through best-of-breed modules as needed (Shepherd, 2006). Standards are an accepted solution for achieving interoperability (Lewis et al., 2008) and are needed for contexts in which an organization produces system-managing content, produces content that will be managed by another system, or purchases content and systems that must interoperate (Shepherd, 2006).

In many domains, standards have already achieved a significant level of interoperability. Every implementation of a standard should be made according to an identical procedure and be completely interoperable with any other implementation. However, this is seldom the case. When they are implemented, they normally undergo customization and extension because the supplier wants to create a unique selling point as a competitive advantage (Lewis et al., 2008). The test to determine the success of a standard is whether it has become so integrated and so much “part of the system” that a user does not reflect on it (Harris, 2001). Table 2 provides an overview of different categories to which specifications and standards belong, and how they support data handling.

Table 2. Standards and specifications categories (Shepherd, 2006)

Type of Specification or Standard	Description
Authentication	Systems that allow authentication of individuals and potentially other systems to single-sign-in across various systems within a larger system.
Content packaging	Allows content and assessments to be packaged for simple transmission between systems containing sufficient information for the recipient system to run the content.
Data definitions	A scheme, comprised of a collection of logical data structures and that defines such things as learner information, competencies, eligibility, qualifications, assessment items, and so on.
Data transport	Describes how data may be moved from one system to another.
Launch and track	Allows content and assessments to be launched and tracked by a management system.
Metadata	Allows content to be tagged, to help management systems search for and discover the content's properties.
Philosophical	Provides a framework for understanding and identifying critical system interfaces.

After this introduction to standards and interoperability standards, the two ISO standards ISO 10303 (also called STEP) and ISO 23247 (Digital Twin Framework for Manufacturing) will be explained. The reason for explaining these two standards in more detail is because they have been investigated and used in the results section, *Ch. 4 Results of Studies*.

2.6.3 ISO 10303 STEP

Computer Numerical Control (CNC) machining systems are fundamental elements of today's production system and include functionalities such as machine and cutting tools, auxiliary and material devices, and fixtures for handling products that are to be machined. CNC machining systems are commonly represented in a digital representation known as a "CNC machine model". The model is a conceptual representation of the machine tool and contains a logical framework representing the machine's functionalities. The CNC machine model contains information that is used throughout a machine's lifecycle and is important to numerous decision-makers in a manufacturing system. Decision-making processes where this information plays an important role are evaluating manufacturing capability, process validation, and production planning (Vichare et al., 2018; Vichare, Nassehi, and Newman, 2009). The machine model consists of a description explaining the overall structure of a machine, the geometric shapes of the mechanical units, and the kinematic relationships between the mechanical units of a machine. For the kinematic relationships, this means defining the existing motion constraints between machine components that are related to each other (Kjellberg et al., 2009). The kinematic information is important when simulating the motions of a machine, as it helps identify any issues sufficiently early for them to be corrected before going to production. Potential issues include tool path errors, collisions between machine components and machined parts, and poor quality machined parts (Vichare et al., 2018; Zivanovic et al., 2017).

Computer-aided (CAx) tools provide a virtual environment in which machining processes may be simulated with a realistic representation of the kinematics, static, and dynamic behavior of a machine tool (Vichare et al., 2018). The current landscape of commercially available CAx tools is broad and provided by numerous vendors. CAx tools serve the same purpose for a manufacturing organization being able to represent and analyze production equipment before going to production. However, the CAx tools provided by various vendors create barriers to sharing and exchanging machine models (plus their kinematics and geometric information) between different CAx systems (Li et al., 2015). Users of CAx tools are limited to the specific CAx format that they use within their organization (or even their function within an organization), and if machine models are recreated in other CAx software, it will entail time-consuming, redundant efforts. This is particularly true as kinematics information is often are rather complex.

Standardization efforts have been made so as to overcome this problem and exchange machine model data between CAx tools in a neutral, standardized format. So far, is it mainly geometric information that is supported and that may be exchanged in a neutral format, according to Standard 10303 of the ISO (International Organization for Standardization), also called the STandard Exchange of Product Data (STEP). This is widely used to support geometric data and various pieces of CAx software have an automatic feature for exporting data to the STEP format (known as a part21 or p21 file). However, there is no implementation that also supports the exchange of kinematic data (Li et al., 2015).

2.6.4 ISO 23247 "Digital Twin Framework for Manufacturing"

"Digital twin" is a term and concept that has recently garnered much interest and hype both within the industry and in the research community. It has existed as a term for around 20 years, and was first used to describe a "digital informational construct of a physical system as an entity on its own." A "digital construct" is the equivalent of a digital twin and represents all the embedded information in a physical system. It is also connected to the physical system throughout its entire life. A digital twin constitutes both a physical and virtual space, with flows of data and information between the two. Data flows from the physical to the virtual space and information from the virtual flowing to the physical space. The information flow may also be indirectly impacted by the involvement of human decision-makers (Grieves and Vickers, 2017). In this case, the physical, or real, space may be a product, process, or system. A digital twin should be able to fully describe the information embedded in either its potential or existing physical instantiation, to fulfill the objectives of a manufacturing problem. A digital twin is a purpose-driven, virtual, complete, or partial representation of the physical reality of a product, process, or system.

ISO 23247 (ISO 2020a), "Digital Twin Framework for Manufacturing," provides a generic guideline, a reference architecture, methods, and approaches for case-specific, digital-twin implementations. This standard can support the composability of models and interoperability between modules. It also explains examples of data collection, communication, integration, and modeling, plus applications of relevant standards (ISO, 2020a). The Ad Hoc group within ISO/TC 184 has attempted to provide a more general definition of a digital twin. It provides two versions of the definition (ISO, 2020b):

Digital twin 1: a fit for purpose digital representation of something designed to support some decisions related to it.

Digital twin 2: a fit for purpose digital representation of some realized thing(s) or process(es) with a means to enable convergence between the realized instance and digital instance, at an appropriate rate of synchronization.

3

RESEARCH APPROACH

Research is a process of systematic investigation, involving concentrated thought that is rational and careful. It should enable understanding and reproducibility, and allow evaluation of the quality of the study (Trochim, Donnelly, and Arora, 2016). The research process should contain clear objectives as to why data are collected and that the collection and interpretation of such data is systematic. A systematic procedure will lead to findings that may elucidate the problem at hand and contribute new knowledge (Saunders, Lewis, and Thornhill, 2016). This chapter explains the systematic procedure adopted in this research to derive its results and conclusions. The chapter explains the worldview and research approach underpinning the research and how studies, research projects, and appended papers help to answer the research questions. The chapter ends with a section explaining how the research was quality-assured.

3.1 PHILOSOPHICAL WORLDVIEW

The term "philosophical worldview" refers to beliefs and values a researcher brings to their research when conducting a study. The researcher's worldview should be acknowledged and made explicit, thus bringing an understanding of the beliefs and values the researcher holds. Acknowledging one's the worldview involves identifying the assumptions that come with a given worldview and relating them to specific elements of a study (Creswell, 2014). In turn, the assumptions about reality made by a researcher impact the choice of methods and methodologies used, shaping the research process (Crotty, 1998; Creswell, 2014). All researchers have a philosophical foundation that influences their research and the knowledge gained during a research study. A researcher is not limited to one worldview and may draw from multiple ones (Creswell, 2014). For the process of formulating research questions, a common source to search is literature already published in the field. Another common source is the experience of a practical problem in a field. For a researcher working in an applied-oriented context, the opportunity to address a real-world problem and make a difference within the field may provide significant motivation for pursuing their research (Trochim, Donnelly, and Arora, 2016).

A key stakeholder of this research is the manufacturing domain; it is from here that the research results and data have been gathered. The research is applied-oriented, examining how manufacturing organizations might become more data-driven. To understand the assumptions made and the motivation for the research questions posed, I will provide a background to my previous experiences and interaction within the manufacturing domain. Prior to and during my Ph.D. studies, I gained experience in the manufacturing field from studies and work placements in Sweden and internationally (Germany and the US). My undergraduate studies were carried out in Mechanical Engineering, latterly focusing on manufacturing. Work experience was gained at an international engineering company with production sites all over the world. Some of the Ph.D. work involved participating in standardization work, in national and international standardization bodies. Besides gaining experiences from another research environment, this was one reason I took part in a research exchange with an American research laboratory, the National Institute of Standards and Technologies (NIST). National and international experience has provided me with many insights into the challenges faced by industry, in terms of both technical and organizational challenges. This has heightened my interest in, and sense of urgency about, providing more knowledge on shaping the future factory, a subject addressed in this thesis.

At its broadest level, a worldview comprises the philosophical assumptions, or "epistemology" of research. These philosophical assumptions explain how researchers gain knowledge and how to create knowledge that is acceptable, valid, and legitimate (Burell and Morgan, 1979; Creswell, 2014). Philosophical assumptions inform the selection of a theoretical standpoint that, in turn, impacts the methodology to use. Methodology includes methods, plus techniques and procedures for gathering, analyzing, and interpreting data (Creswell, 2014). The research in this thesis uses the mixed methods approach. It combines qualitative and quantitative research methods, and its typically associated worldview, pragmatism. The pragmatic worldview characteristically focuses on investigating the consequence of actions by adopting a problem-centered focus (Kelemen and Rumens, 2008). It is pluralistic and has a practical, real-world orientation that explains "what works." Of primary importance are the questions raised rather than the methods used (Creswell, 2014). Research that is conducted in alignment with the pragmatic worldview is initiated by identifying a problem. A pragmatic worldview normally applies multiple data collection methods. Table 3 provides a summary of the pragmatic worldview in terms of ontology, epistemology, axiology, methodology, and rhetoric.

The research in this thesis is applied-oriented, taking a stance on a problem that has been identified in reality. For most companies, digitalization in manufacturing is still not a straightforward endeavor and more research is needed to investigate and explore how new technologies may be used to create value for manufacturing. This is supported by this thesis' two research questions, that investigate data requirements depending on the manufacturing system lifecycle decision and how data-sharing may be supported by interoperability standards. The main focus of the research is to address and answer these questions; thus, a method will be selected that can support this. On this basis, applying mixed-methods research that combines qualitative and quantitative research methods would provide suitable support for collecting data that can answer the research questions. Compared to the worldview, the theory operates at a narrower scale and provides a general explanation of what a researcher may expect to find in a study (Creswell, 2014). Theory-building will therefore be explained in the next section, *3.2*.

Table 3. Elements of the worldview pragmatism and the implications for practice (adapted from Creswell, 2014)

	Philosophical Question	Pragmatism	Description
Ontology	What is the nature of reality?	Singular and multiple realities	Researchers test hypotheses and provide multiple perspectives.
Epistemology	What is the relationship between the researcher and that being researched?	Practically	Researchers collect data by “what works” to address the research question
Axiology	What is the role of values?	Multiple stances	Researchers include both biased and unbiased perspectives
Methodology	What is the process of research?	Combining	Researchers collect both quantitative and qualitative data and mix them
Rhetoric	What is the language of research?	Formal or informal	Researchers may employ both formal and informal styles of writing

3.2 THEORY-BUILDING

Two main branches are relevant in describing how theory is created; deductive and inductive reasoning. Inductive reasoning means starting with something specific to contribute to general theory-building, and is open-ended and exploratory (Trochim, Donnelly, and Arora, 2016). Theory built from this type of reasoning always takes a stance based on observation. This means starting with data collection. A researcher using inductive reasoning will be interested in exploring a phenomenon in the context in which it occurs (Saunders, Lewis, and Thornhill, 2016). Deductive reasoning starts from the opposite side, going from the general to something more specific. It is narrower by comparison with inductive research and its objective is to test or confirm hypotheses (Trochim, Donnelly, and Arora, 2016). Deductive research involves deriving conclusions that fulfil premises defined for a study. In the deductive approach, when premises are termed “fulfilled” and “true”, conclusions also are termed true (Ketokivi and Mantere, 2010). In pragmatically-aligned research, it is possible to combine both deductive and inductive thinking. This is because the pragmatic view combines qualitative and quantitative data (Creswell, 2014).

As explained in previous section, this research had its roots in an identified real problem that needed more investigation to support the manufacturing field. This triggered an interest in exploring the area and the existing literature on the topic. The literature was also found to have identified this as a real problem, but did not provide many solutions as to how it might be solved or put forward any real examples as to how it might be addressed. Therefore, the studies in this thesis were designed based on the specific real problem. The approach was more general when conducting a literature search, but became more specific during the studies. Supported by the literature, the specific findings were then made more generalizable for companies in the same area. This was done to provide best practices and insights into using digital technologies in manufacturing and creating value for the organization. The research may be characterized as moving back and forth between deductive and inductive, in keeping with common practice in pragmatic research.

3.2.1 Literature Study

Figure 1 offers a general explanation of how the literature supported the studies conducted and results obtained. The cornerstone of this thesis is exploring how a transformation from reality to data creates decision support for a decision-maker working in production. During a transformation, more fact-based decision support is created. This should support a decision-maker in creating an understanding what is happening during processes and in the reality of the production system. In explaining this process, a number of topics were identified as relevant. These are: 1) manufacturing systems, 2) digital technologies, 3) differences between data, information, and knowledge, and 4) big data (and its terminology relating to volume, velocity, and variety). Beyond these initial topics, an additional one that became relevant to include was standards and interoperability standards. Since this research is motivated by ongoing change in manufacturing, it was relevant to examine the definitions of Industry 4.0, SMS, and CPS.

The literature search was conducted mainly by using the Web of Science and Scopus databases. In cases when a specific reference was searched for (or to learn more about publications from a given researcher), Google Scholars served as the database. To evaluate the relevance and quality of papers, the journal and citation served as a criterion. However, relevance was also established based on the paper's abstract and title. Cross-referencing between papers and authors was a useful tool in finding relevant papers.

Some papers were particularly important to this research and for building the theoretical framework. These are; a paper from Hilbert and López (2011) published in Science and defining the key functionalities of digital technologies. A paper from McAfee and Brynjolfsson (2012) in Harvard Business Review (HBR), explaining the change that will be seen in businesses that apply big data. A report published by NIST on SMS and the associated standardization landscape was written by Lu, Morris, and Frechette (2016). There was also a the report from Kagermann et al. (2013), presenting the fundamentals of Industry 4.0.

Beyond published the peer-reviewed literature, important sources were also white papers and reports published by consulting companies, such as McKinsey & Company, Boston Consultant Group (BCG), and the World Economic Forum (WEF). Since standardization and standards was an important topic, the standardization bodies' publications on standards were also significant. These included the Swedish Institute for Standards (SIS), International Organization for Standardization (ISO), and Deutsches Institut für Normung (DIN).

3.3 RESEARCH APPROACH – MIXED METHODS RESEARCH

A pragmatic worldview best suits the purpose and view of this research since it aims to answer the research questions using the most appropriate methods, without being bound to any specific research method. A pragmatic worldview allows methodology to be combined and a researcher may apply a mixture of quantitative and qualitative data collection methods. Qualitative research collects more open-ended data, while qualitative research seeks to explore and understand the meaning of the individuals or groups that may be associated with a social or human problem. Quantitative research tests objective theories by examining the relationships between identified variables. Data collected by quantitative measures are close-ended. Both qualitative and quantitative data collection methods have some inherent strengths and weaknesses in the way they answer research questions. Mixed-methods research combines them to get the best out of them while reducing their limitations. By being combined, mixed-methods may provide a more detailed description of the research problem (Creswell, 2014). This suggests that mixed-methods research was the most suitable way to conduct studies for this thesis.

The studies in this thesis were conducted according to mixed-methods research, combining quantitative and qualitative data collection methods. This combination of quantitative and qualitative research is summarized in Table 4, with appended papers and research projects. Papers 1 and 2, project A, start quantitatively and end qualitatively, providing answers to RQ1. Paper 3, project C, is a quantitative study exploring and answering mainly RQ2 but also providing some insights into RQ1. Papers 4 and 5, project B, are qualitative studies answering RQ1 and 2. Paper 3 is a study of how to support more interoperable information exchange using standards and involves the development of a solution to support this. The insights gained from this informed Papers 4 and 5. These explore the topic using qualitative methods to understand the perspective of practitioners in this area. Most of the studies in this research started with a quantitative stance, exploring how new digital technologies may be applied and used to provide more data on a production system. The second phase of the research required more insights into how this may provide value to a manufacturing organization. It was thus necessary to understand how practitioners in manufacturing think. This, in turn, has motivated the use of qualitative data collection methods to understand how practitioners in this field consider that data supports them in decision-making and how interoperability standards may enable information exchange and reuse. This way of working and combining quantitative and qualitative studies is called "sequential mixed methods"; quantitative data are collected first and then supplemented by qualitative data (Creswell, 2014).

Table 4. Mixed methods research mapping projects and belonging appended papers and corresponding research question answered

Project	Paper	RQ 1	RQ 2
A	1	Quan. & Qual.	-
A	2	Quan. & Qual.	-
C	3	Quan.	Quan.
B	4	Qual.	Qual.
B	5	Qual.	Qual.

The timeline of this thesis, with projects its and papers, appears in Figure 9. My Ph.D. journey began in August 2016 and will conclude in September 2021. During this timeframe, the research was carried out under three projects, resulting in five papers appended to this thesis. Halfway through, in February 2019, a Licentiate thesis was published and defended; this also had six appended papers and presented the scope of the research. Paper 1 summarizes the results of the Licentiate thesis, based on the work and results of Project A, active during 2016-2018. Project B overlapped the first and second parts of the Ph.D. and provided data for Papers 3, 4, and 5. The second part of the Ph.D. was also carried out at NIST in the US. This comprises the work under Project C and provided input to Paper 2.

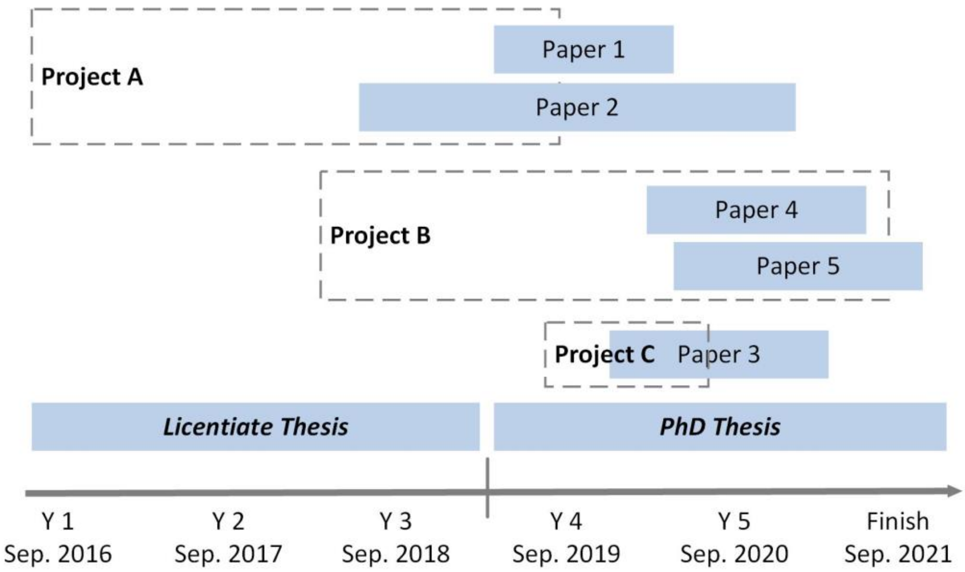

Figure 9. Timeline of research with research projects and appended papers

Project A was a collaborative project between the academic partner, Chalmers University of Technology, telecommunications and ICT provider Ericsson, and bearings manufacturer SKF. The project aimed to investigate opportunities for having a connectivity solution in a production setting that could provide available and reliable communication. Ericsson provided a 5G network connectivity solution (4G LTE with 5G characteristics). The production test location were SKF's world-class manufacturing workshop and Chalmers' Smart Manufacturing Laboratory, both situated in Gothenburg. A production setting poses new requirement types that must be considered when implementing a connectivity solution involving network availability and low latency. Many of the requirements are one for which the promises of 5G are well-suited to a production setting. 5G can support mobility of equipment and personnel, time-critical operations, and handling of a large amount of data. Accordingly, this project formulated four demonstrators to showcase the opportunities of 5G; designing and planning a 5G network, stationary connectivity, mobile connectivity, and network and cloud. Design and planning a 5G network involved an offline planning procedure that can plan availability and reliability in a virtual representation of the production setting. Stationary connectivity involves fulfilling the requirements posed by fixed-position equipment. Mobile connectivity needs to fulfill the requirements introduced by humans and equipment moving in a production system introduce. Network and cloud involved the deployment of a 5G solution for a production system setting. Each of these demonstrators was designed to be scalable and relevant to the different lifecycles of a production system. The results, with appended Papers 1 and 2 will explain the demonstrators in more depth.

Project B is a project called Digitala Stambanan (National Digital Highway); a two-year research and innovation project in Sweden. It involves both discrete manufacturing and the process industry, because, even though the two industries differ, this project is aiming to create joint efforts towards understanding the needs of Swedish manufacturing industries regarding digital technologies and infrastructure. Understanding the future direction in terms of using technology and opportunities to create new ways of doing business means documenting the current state. This is achieved through cases involving manufacturing companies, technology providers and experts, and academia. Large enterprises and small and medium-sized enterprises (SMEs) were involved. All cases focus on supply chains with several companies involved in each one. Findings are made in each supply chain with some of them case-specific. However, the project aims to identify common challenges that can be generalized. This project resulted in Papers 4 and 5. Both papers focus on the digital twin concept and investigate the perspective of practitioners. The work was based on an interview study with representatives of the manufacturing companies involved in the project.

Project C was conducted in the context of a research exchange at NIST's Systems Integration Division, supporting their Model-Based Enterprise (MBE) Program. The project involved developing a solution for the exchange of machine model data in a standard format to support information reuse and interoperability between proprietary formats. There are already ISO standards that support the exchange of machine model data in a standard format. However, because of the complexity of kinematic data, convergence to a standard format is not complete and therefore the use of standards is still lacking. For most companies, thins normally means they need to use numerous software to comply with their customers. Paper 3 presents the solution that was developed, and discusses the opportunities and challenges of exchanging data in a standard format.

3.3.1 Data Collection Methods Used for Answering the RQs

This section presents the data collection methods used to answer the research questions. It is based on the research questions, with the section showing how projects and papers have supported answering them. The data collection methods are finally summarized in Table 5.

RQ1) *How do manufacturing system lifecycle decisions influence the requirements of data collection towards interoperability?*

To understand the requirements for manufacturing system lifecycle decisions, it was deemed important to interview the subject-matter experts at the organization and gain a more comprehensive understanding of the research problem. Thus, the study presented in Paper 1, began by collecting field data aided by digital technologies. The second step involved focus-group interviews to evaluate the benefits from the subject-matter experts' perspective. The respondents in the focus-group interview were regarded as receivers of the collected data. Questions to this group were inspired by the literature with an emphasis on literature that explained the big data concept. Paper 2 is from the same project; the study is also included in Paper 1, but with fewer details. The study in this paper takes a different approach, intending to explain knowledge and lessons learned from the quantitative part of the study. This study, therefore, includes observations made by the researchers in evaluating the benefits of having more decision-making data available. Observations include field note, consisting of documentation in the form of meeting minutes and the various steps used in the analysis to answer the research questions. Papers 4 and 5 (conducted as an extension of paper 3) also provided insights into RQ1, as they were investigating the manufacturing system lifecycle decisions for which digital twins are most applicable and best suited when supporting a manufacturing organization. How Papers 4 and 5 were carried out is explained further in the next section, on the data-collection used in answer to RQ2.

RQ2) *What makes interoperability standardization applicable to sharing data in a manufacturing system's lifecycle?*

To answer this question, a quantitative study was first conducted. This was to develop a solution to enable extended use of an existing interoperability standard for better information exchange and reuse. This solution has relevance and implications for industry but was developed as a case study to understand how the existing interoperability standard might find more use. The development involved handling two data streams extracted from the same software but containing different data (kinematic and geometric), describing the production equipment in the virtual environment. These were then combined into a single data-set translated into the standard neutral form used for this case. The development and results are presented in Paper 3, Project C.

The standard applied in this case has been around for many years and is, to some extent, also used in manufacturing as an integrated feature of the software. However, if some of the data points are intended to make the representation complete, its use remains limited. This hampers any opportunity for information exchange and reuse. This motivated further investigation of what makes interoperability standards (and standards supporting the digital representation of production equipment and systems) applicable for use in manufacturing. Papers 4 and 5, therefore, followed this up by investigating the use of interoperability standards to support the manufacturing domain. It was carried out in the context of Project B, including a total of three value chains and twelve actors. These companies were visited as part of the project. A good understanding of their current situation was gained, including following their production flows and having in-depth discussions regarding their digital maturity and method of handling data.

To answer the research question, in-depth interviews were organized with representatives from six of the participating companies. Five manufacturing companies were represented belonging to two supply chains. One trade organization was also interviewed, representing hundreds of SMEs that supply the automotive sector. Interviews were planned for 30 minutes and were recorded and then transcribed by the same researcher who conducted the interviews. An analysis of the interviews was completed with other researchers, to check what the respondent's answers might say about the practitioner's understanding of how digital twins may support in the manufacturing domain and how interoperability standards can support this. Table 5 summarizes the research design and data collection methods used for the respective papers appended to this research, as explained in this Section *3.3* of the thesis.

Table 5. Summary of the papers with selected research design and methods for data collection

Project	Paper	Research design	Data collection methods
A	1	Experiment Interviews	Deployment of a new connectivity solution and connecting production equipment and personnel Focus interviews
A	2	Experiment Observations	Measurements and simulation Field notes
C	3	Experiment	Technical development of a Java-based application
B	4	Observations Interviews	Plant visits Semi-structured interviews
B	5	Observations Interviews Literature review	Plant visits Semi-structured interviews Definition in the literature of Digital Twin and summary of applicable interoperability standards related to ISA-95

3.4 QUALITY IN RESEARCH

Deciding on a research design is not just about using data collection methods that best answer the research questions; it also involves considering ethical issues and the possible constraints of a research design (Saunders, Lewis, and Thornhill, 2016). Several aspects of a research study should be quality-assured; planning, design, data, interpretative rigor, reporting, and utility. *Planning quality* means evaluating the feasibility, transparency, and position of a study in the existing literature. *Design quality* covers how detailed the description of the study design is and how well the data collection methods complement each other. *Data quality* means that the methods of sampling, data collection, analysis, and integration are appropriate, adequate, and rigorous. *Interpretative rigor* means that the findings emerge from data collection methods, any inferences align with the findings, any inconsistencies in a study are explained and that, if possible, the conclusions should be interpreted in the same way by others. *Reporting quality* refers to a completed study with clear reporting and that can yield an understanding that surpasses the sum of the study's parts. Lastly, *utility* means that the results will be usable by the receiver (O'Cathain, 2010).

Some other aspects that should be considered when quality-assuring research are the *validity*, *reliability*, and *generalizability* of a study. *Validity* means determining whether the findings are accurate from the perspective of the researcher, participant, or receiver of a study (Creswell, 2014). In qualitative research, validity involves applying certain procedures to ensure the accuracy of the findings, and employing strategies to address any threats to the quality of the research (Gibbs, 2007; Creswell and Clark, 2018). *Reliability* in qualitative research is an indicator of whether the researcher's approach is consistent across research studies and projects (Gibbs, 2007). In general, reliability is about examining the stability of a study (Creswell, 2014). *Generalizability* relates to external validity when applying the results of a study to a new setting, new people or new sample (Creswell, 2014).

Mixed-methods research combines quantitative and qualitative data collection methods. It attempts to retain the positive aspects of each method while reducing their limitations. In other words, it tries to get the best out of each method. The definition of high quality in quantitative and qualitative research methods varies. Quality in quantitative research is termed by the *reliability* of a study, meaning how repeatable it is. In qualitative research, this is referred to as the *dependability* of a study, and translates to the degree to which the same results may be observed multiple times. Quality in qualitative research also includes the *credibility* of a study. Credibility in a qualitative study must be confirmed by a study's participants, as they are the only ones who can determine whether the results are believable. *Confirmability* is a quality measure for the results obtained and the conclusions drawn. Its aim is to reduce any bias in a study. There are strategies for increasing confirmability, such as triangulation and running data audits to examine data collection and analysis procedures (Trochim, Donnelly, and Arora, 2016). Other ways of ensuring high quality in mixed methods studies include rigorous evaluation of the collection and analysis of quantitative and qualitative data in response to research questions and hypotheses. High quality in mixed-methods research also intentionally integrates quantitative and qualitative data and results. Each mixed methods design is specific to its inherent logic and its intent to obtain certain types of inferences (Creswell and Clark, 2018). The ways in which this research was quality-assured are explained and evaluated in the discussion.

4

RESULTS OF THE STUDIES

Results are organized based on topic areas with results from the appended papers and are included here to answer the research questions. The topic areas are: 1) Connected Factory, 2) Standard Representation of Machine Model Data, and 3) Digital Twin for Smart Manufacturing. The Connected factory section includes two topics "Designing Connectivity for a Factory" and "Connected Machine and Human." The standard representation of machine model data presents an approach to translating machine model data into a neutral form. The Digital Twin section is divided in the two subsections, "Definition of Digital Twins from a Practitioner's Perspective" and "Vision for Digital Twins in Manufacturing Supply Chains."

4.1 CONNECTED FACTORY

The two studies presented here were conducted during Project A, that investigated the applicability of new communication technologies in a manufacturing setting. The project constitutes of four demonstrators, developed to answer how the emerging 5G communications technology may be used in a manufacturing setting. The demonstrators were developed and implemented in both a real manufacturing system and a Smart Manufacturing (SM) laboratory. The two studies presented are: 1) How to Design a Connectivity Solution for a Factory in an Offline Environment and 2) Connecting a Machine to Enable More Production Data to inform Decision-makers in the Production System.

4.1.1 Designing Connectivity for a Factory

Mobile cellular networks are used in both outdoor and indoor environments, with different requirements and prerequisites in deploying them. The factory environment is a new and, as a yet, largely unexplored area. Factory environments are distinguished by a number of aspects when compared to deployment outdoors and to mention some: 1) a factory setting involves machine equipment allocated to dense areas, with materials and characteristics that may have the effects of scattering radio waves, 2) time-critical operations in a factory need ensured availability to communication, 3) there is a freedom of where the equipment can be placed, and 4) installations or changes in a factory should be kept to a minimum. Thus a new way of planning the systems prior to deployment should be developed, to ensure a connectivity solution can meet the requirements of a manufacturing system. The idea of this demonstrator is to plan networks using a virtual representation of the factory environment, capturing information on the placement of equipment and material. The demonstrator approach was developed as four steps, shown in Figure 10.

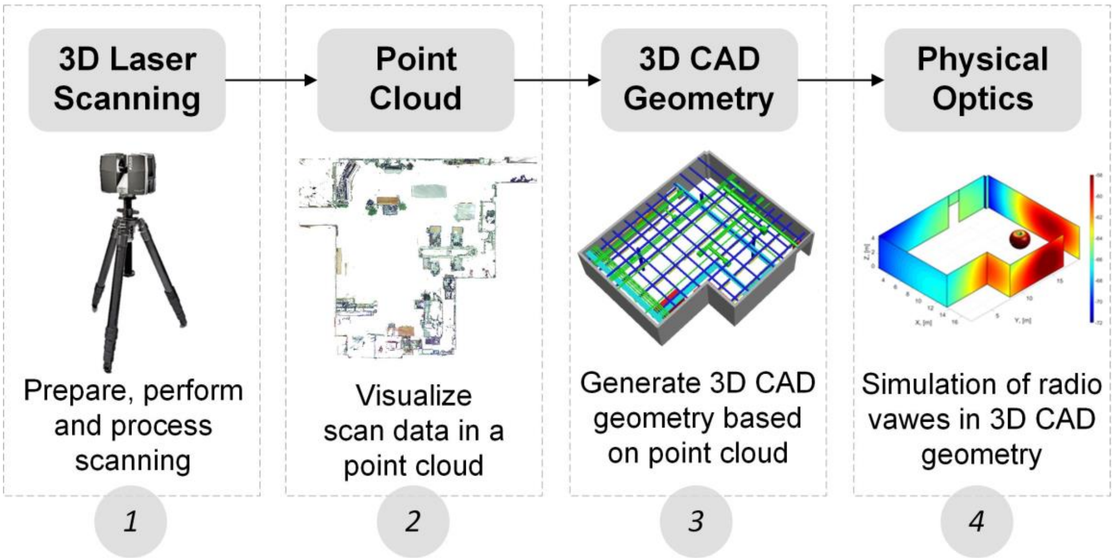

Figure 10. Approach for planning a cellular network in a virtual environment including Steps 1-4; Steps 1-3 for collecting the spatial data of the production system and visualizing it virtually and Step 4 for performing network planning

Depicting a physical setting in a virtual representation (such as a factory or production cell) is becoming more common. This is largely because capturing spatial data from an object or room is now easy to do, aided by 3D laser scanning technology, also called "light detection and ranging" (LiDAR). 3D laser scanning is a non-contact method, meaning that there is no physical contact with the surface from which it collects data. Active sensors capture spatial data in three dimensions, plus associated color data (Varady, Martin, and Cox, 1997). A laser collects spatial data by sweeping the environment to be represented; the data are the saved as 3D point clouds (Berglund, Lindskog, and Johansson, 2016; Klein, Li, and Becerik-Gerber, 2012). This study used 3D laser technology from FARO Focus 3D.

Figure 10 presents Steps 1-3, showing how to collect spatial data using 3D laser scanning and how to visualize that data in a 3D environment. Step 1 is the collection of spatial data by 3D laser scanning. This study was conducted in Chalmers Smart Industry (CSI) lab, that has an LTE network with 5G characteristics, comprising two Radio Dots and one radio base station. The activities in Step 1 are summarized in Table 6.

Table 6. 3D imaging capture and processing data from Step 1 (Bärring, 2019)

Number of scans	**Million data points**		**Data Size**		**Time duration for**	
	Per scan	**In total**	**Raw files**	**Processed**	**Capture**	**Processing**
10	10*10^6	100*10^6	650 MB	1,1 GB	3h	3h

Step 2 represents spatial data collected in a 3D environment using Autodesk ReCap software. ReCap can process the scan files with spatial data and generate a point cloud representing the scanned 3D environment. It can also allow that point cloud to be imported into a Computer-Aided Design (CAD) environment. One obstacle encountered in this work was the requirement for solid surface. When ray-tracing, these are required to produce ray-based simulations for network planning. This was not the intended approach, but since ReCap provided an opportunity to represent the point cloud in a CAD environment, it was possible to transform the factory environment (CSI-lab) from a point cloud to a CAD representation that was usable in Step 4 (ray tracing). This is indicated by Step 3 in Figure 10. The transformation was done manually, adding solid CAD objects while using the point cloud as a reference.

Steps 1-3 also involved gathering information on material and objects from the environment as this may impact the scattering effect. The laboratory was used mainly for teaching but also included a CNC machine and conveyor paths to simulate production flows. The total area represented corresponds to 14.5 by 18 m (about 261 m^2) and has a ceiling height of 3.0-4.6 m. Materials included steel and sheet metal, sound-absorbing material covering the ceiling, and plaster on the first layer of the walls. The floor was concrete with a layer of plastic. A more detailed view of Steps 1-3 appears in Figure 11, visualizing the richness of the spatial representation that may be achieved with 3D laser scanning.

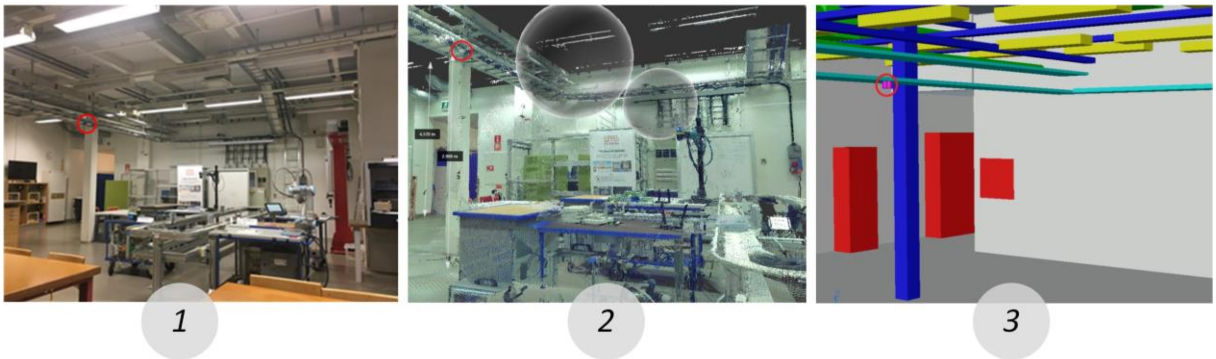

Figure 11. The three steps of capturing the spatial data from reality using 3-D laser scanning to a CAD representation. (1) Photo of CSI-lab; (2) point cloud of CSI-lab; and (3) CAD of CSI-lab. The circle in red in the upper left corner marks the Radio Dot location (Bärring, 2019)

Step 4 is point at which the actual network planning is carried out using ray tracing, also called physical optics (PO). This is a hybrid PO developed for multiscale reflector antenna systems (Iupikov et al., 2014). This demonstrator investigates the idea that network planning may be done in a virtual environment. Thus, some simplifications were made to the simulation so that the study would be a time-efficient initial test of the approach:

1) geometries (for example walls, floor, and ceiling) were simplified by only using flat and slowly curved surfaces;
2) the materials for objects forming part of the simulation were assumed to be perfect electric conductors;
3) mutual coupling effects resulting from the scattering of radio waves between walls were assumed to be negligible, and;
4) the radio source was assumed to have a Gaussian pattern (linear polarized) with the tapper –1 dB at $\theta = 90°$.

MatLab was used as a simulation environment for the PO method. The reader is referred to Iupikov et al. (2014) and Iupikov (2017) for more information on the PO method used. The settings for the simulation are summarized in Table 7.

Table 7. Simulation parameters setting

Simulation parameter	Setting
Frequency setting of interest	2.365 GHz
Size of the EM-problem	~332000 mesh cells with a size of ~42×42 mm (~0.33×0.33 wavelength)
No. of radio sources (radio dots)	Two dots at different positions on the ceiling, operating either one by one or simultaneously.
EM model	The environment consists of 10 walls.
E-field power distribution	Calculated the measurement path data to enable comparison.

The applicability of the approach was evaluated as a final part in determining how well the simulation represents the network performance. This was done by comparing the results of the simulation with measurements taken in the real environment (CSI-lab). The measurement was conducted using a TEMS Pocket LTE cell phone operating in the B40 band. A comparison between simulation and measurement results appears in Figure 12, showing a scenario in which one of the Radio Dots is active. Figure 12a represents the simulation and Figure 12b the measurements. In the figure, the color scale indicates the signal strength. As may be seen, the comparison is the result of simulations and measurements corresponding to the same signal strength at the same distance from the Radio Dot. This shows promising results for the idea being investigated; that network planning may be carried out in a virtual representation of a factory environment before deployment. Based on the results of Step 4, a network plan has been developed to support deployment of the network in a factory environment and ensure a reliable, available network with minimal disturbance to the production system.

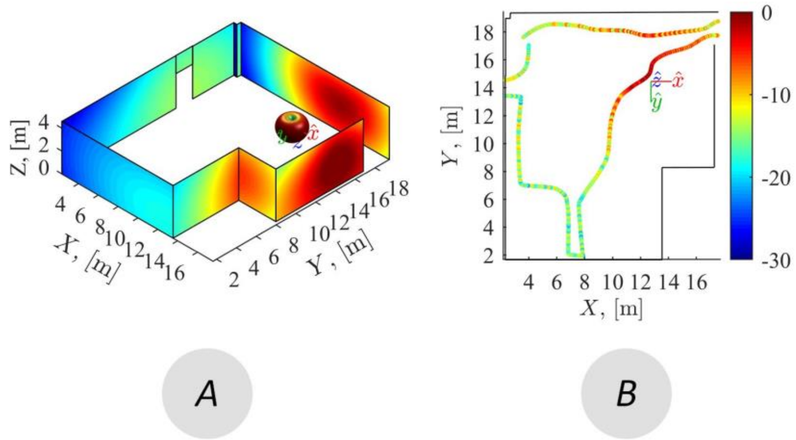

Figure 12. The magnitude of the E-field (A) on a plane elevated 1 m over the floor and on a vertical Y-Z plane and (B) along the measurement path in decibels (Bärring, 2019).

4.1.2 Connected Machine and Human

The second study (of how 5G communication can serve needs and requirements in a manufacturing context) is also the second stage in the design and deployment of the network. This is an investigation the applicability of 5G communication, showing how the promising characteristics of 5G may benefit the manufacturing cases. This study was defined in a demonstrator in which both production equipment (machine) and a decision-maker (human) are connected to the 5G network. It may also be explained as demonstrating connectivity in the case of stationary (machine) and mobile (human) connectivity. Stationary, in the sense of a fixed position, and mobile, in the sense of moving around within the factory environment. The stationary connectivity case was represented by a CNC machine and the mobile connectivity by a human operator equipped with a smartphone featuring a mobile operator support system (MOST). Before these two connectivity examples are explained, the common communication infrastructure should be clarified. The overarching plan of the connectivity solution, with the ability to support communication, computing, and storage of data, is demonstrated in Figure 13. As described for designing a network, the connectivity solution is a dedicated 4G LTE network with 5G characteristics. Both stationary and mobile connectivity solutions are included in Figure 13.

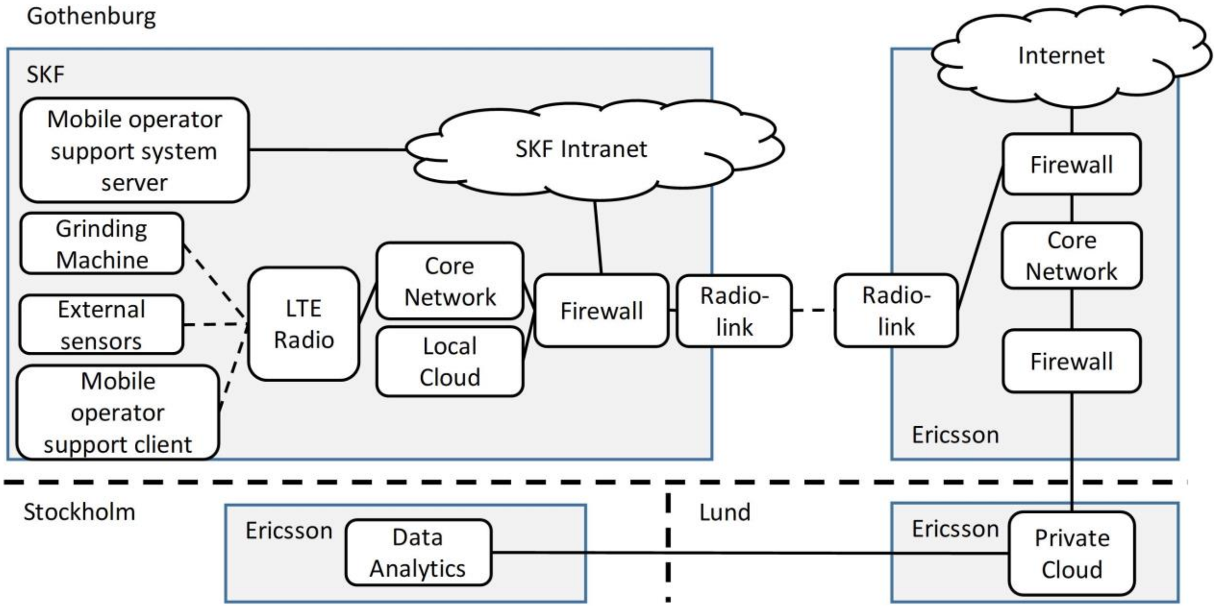

Figure 13. The infrastructure of the connected machine for the 5G testbed project (Bärring, 2019)

LTE modems were used to establish both stationary and mobile connectivity for communication over the cellular LTE network. The Calvin distributed IoT platform was used to handle and store data centrally, while a local client-server was used for decentralized handling, stored internally at the workshop. The database, or cloud, was located in Lund, Sweden and the analytics platform for analysis and anomaly detection was located in Stockholm, Sweden.

The machine connected in this case has three main critical machine components that impact the performance and even the quality of machined products. These are the ball screw, slides, and motor. If information on these components could be made available when they are worn out and need attention, decision-makers could be supported in making decisions that will ensure high levels of machine performance and availability. The subject-matter expert in the manufacturing setting decided to focus on the specific machine components, so as to provide more data and thereby decision support. Data points concerning these components were collected from both the machine computer (the “grinding machine”) and the added external sensors, as depicted in Figure 13. The data collected and how it was accomplished are summarized in Table 8.

Table 8. Data collected (data), how the data is collected (data collection), and exchanging data (communication protocol). All data types are collected at a frequency of 100 ms.

Data	**Data collection**	**Communication Protocol**
43 individual tags from the machine	PLC	Open Platform Communications Unified Architecture (OPC UA)
Vibration data	IMx – vibration measurement	
Cooling fluid and temperature	IO-Link	Transmission Control Protocol (TCP)
Temperature	Raspberry Pi (RPI)	Any communication system that supports the Linux platform

The data points collected from the machine computer and by the external sensors added to the CNC machine comprised 43 individual tags on the machine vibration, cooling fluid, and temperature. Data from the machine may be collected by the Programmable Logic Controller (PLC) and the extra sensors added externally to the machine are commercially available industrial items. The externally added sensors included a vibration measurement solution called IMx, two sensors to collect cooling fluid and temperature data over the IO-Link protocol, and a temperature sensor embedded in a Raspberry Pi (RPI). The data collection frequency was every 100 ms. The communication protocols used were OPC UA, TCP, and any communication system that runs on the Linux platform.

The database (cloud) is of the “not only Structured Query Language” type (noSQL), implying that it can handle different types of data (Rajkumar et al., 2010; Renwick and Bason, 1985). Apache Hadoop (OpenCV, 2018) and Kafka (Esmaeilian, Behdad, and Wang, 2016). This was used to distribute data, with data stored as JavaScript Object Notation (JSON). Luminol’s Library was used for data analytics. This is open source at Github and suitable for handling continuous and seasonal data. The data analysis in this study focused mainly on detecting anomalies in vibration data. Vibration data were collected from eight sensors. Anomalies could be identified in all of them, with the daily anomalies figures varying between 5 and 50.

Mobile connectivity was demonstrated suing a smartphone with MOST; operators working closely with the machine are equipped with these. The purpose was to offer both real-time and analyzed data to operators in the MOST system, and provide decision support based on data. MOST has functionalities present data on the three critical machine components that were identified. MOST supported the publish-subscribe protocol Message Queuing Telemetry Transport (MQTT) that is popular in IoT applications (Weichhart and Wachholder, 2014). The three functionalities developed for MOST to visualize data on the three critical machine components were; tolerance offset, vibration data, and cycle time, as explained in Table 9.

Table 9. The three functionalities developed for MOST with description (Bärring, Johansson, and Stahre, 2020)

Functionality	Description
Tolerance offset	Informs if there should be any adjustment made in the machine because of tolerance offsets that have appeared in the previous product. Based on the displayed value, an operator can take action to compensate for a tolerance offset by pushing either a plus or minus compensation.
Vibration data	Presents vibration of spindles and motors in the machine in real-time. Changes in the vibration are a good indication of a possible problem that could occur in the machine, which can have a severe impact on the quality of the product.
Cycle time data	Presents the actual cycle time for each machined product. This information is intended to give insights into the variation in cycle time that can have an impact on productivity.

To understand how the data made available to operators can support them in their decision-making, decision-makers from various roles and responsibilities in production were interviewed in a focus group interview. The first two questions concerned how they consider the applicability of the functionalities developed in MOST might support them in their work, now and in future. Their answers are summarized in Table 10.

Table 10. Results from the evaluation of the tolerance offset, vibration data, and cycle times by domain experts (Bärring, 2019)

Data	Today	In the future
Tolerance offset	• Supports flexibility and mobility of an operator • An operator can be informed and act regardless of the location in the workshop	• Even more important to be able to monitor a machine anywhere in the workshop
Vibration	• Fewer unplanned stops because of machining errors • Used to understand the lifespan of a tool	• Be able to plan better and avoid unplanned stops
Cycle time	• Of interest to managers and production technicians for follow-up • Used to understand how the designed system performs in reality	• Will provide a historical basis to support continuous improvements

From the results presented in Table 10, all functionalities are determined as relevant to decision-making both now and in the future. Some differences were identified, depending on which MOST functionality was more important to a specific decision-maker. Tolerance offset provides an operator with information so that they are always aware if the machine is working close to the known tolerance offset. If the machine goes outside this tolerance offset, the result will be products with quality defects. Given the opportunity to have this information available anywhere, the machine operator may take the required action to avoid the machine straying outside the tolerance offset. Operators' flexibility and mobility will increase, as they will have this information available at any time; something that is deemed even more important for the future. Vibration is already a widely-used data point in this production organization, for understanding the state of a machine and whether maintenance or proactive measures are needed. Up to this point, vibration data has mostly been collected manually. This solution means that vibration data may be presented via a digital interface and can also be stored over time, so as to gain historical data. The main benefits of having this data as decision support mentioned by the interviewees is that they can better plan the availability of production equipment and avoid unplanned stops, both now and in the future. Another aspect is that they can analyze the lifespan of tools purchased from external vendors. The cycle time is not as crucial a data point for daily operations. Rather, it provides an opportunity to compare the designed system with the actual outcome in terms of cycle time. In future, this information will provide a basis and background for making continuous improvement, because the historical data will be available.

An additional topic that was addressed during the interview was the characteristics of big data, i.e., volume, velocity, and variety. Just as the functionalities of MOST are important now and in future work, the different aspects of big data were investigated based on their current relevance and the future scenario envisaged by the decision-makers. An initial question was also raised, to understand the decision-makers' current way of making decisions. They were asked whether they tend to rely mostly on data or their intuition when making decisions, and whether they foresee any changes in future decision-making. The answer to this question plus the volume, velocity, and variety of data are summarized in Table 11.

Table 11. Results from evaluation with a focus group on the topic of big data (Bärring et al., 2018)

Question	Current state	Future state
Data or intuition	Mainly based on intuition. Maintenance has started to collect more data.	More data-driven decision-making.
Volume	For production technicians and maintenance, it is the volume that will play an important part to drive decision-making.	More data will become increasingly important as the organization learns more from the data.
Velocity	It is important for daily decision-making.	For the operator, the speed of data will be important.
Variety	Data sources used today are a system where the operators manually add status information when the shift is finishing. There is also oral communication between the personnel.	A variety of data sources will be important in the future, to extract and analyze data from various sources for analysis and decision-making.

As can be seen from the answers in Table 11, decision-making has relied mainly on the intuition of people in the organization, and they have not focused much on the three Vs of data. However, as they understand the future manufacturing system, they foresee the need for more data and would like to become more data-driven and data-oriented in their decision-making. An additional aspect that was pushed during the interview was the importance of having the right data available at the right time to take the required actions. The lesson learned from Project A (of which this study was a part) was that if data are not presented at the right resolution they may not provide the intended insights. This further emphasizes the importance of working cross-functionally and closely-allied with IT and subject-matter experts to iterate the results quickly. The interview also covered the trade-off between speed and quality of data. Whether any of the aspects were deemed more important than others depended on the situation. When fast action is required, it may be more important to know that something has happened rather than the fine details of what has happened. On the other hand, when the root cause of an error or event is needed, then data quality becomes important in understanding it.

4.2 STANDARD REPRESENTATION OF MACHINE MODEL DATA

To provide a solution to the standard representation of machine model data explained in Section *2.6.3*, an approach was developed to explain in general terms how geometric and kinematics data can be exported to the standard format (defined by STEP) so that it can be exchanged between different CAx tools. The general approach is presented in Figure 14 and starts with a machine model defined in a CAx tool, containing the geometric and kinematic information on the machine model. As stated earlier, most CAx tools already have an automatic feature for exporting geometric information to the STEP AP242 format, but the extraction of kinematics information is either not yet supported or not implemented. However, much CAx software does provide features (an interface or adapter) for interacting with an information model and may support such things as the extraction of kinematics information. Examples include J-Link for PTC Creo and NX Open for Siemens. Thus, the approach includes a second step called *a STEP generator* that will combine the data set with geometric information defined in AP242, plus a data set including the kinematic information. The Application Programming Interface (API) Java Standard Data Access Interface (JSDAI) was used in the *STEP generator* to translate the two data sets of geometric and kinematics data into one complete machine model in STEP AP242 format. This translation in the *STEP Generator* may also require some additional information to be completed for the machine model representation in STEP, and may include user input. Hence, the "extra information" in Figure 14. Following the *STEP generator* in the general approach, the intention is that this procedure should provide a complete description of the machine model in STEP AP242 format. This makes it possible to exchange the machine model between various CAx tools. The last two steps of the approach illustrate to "exchanged between different CAx tools." This feature was not included in the development to support decision-making.

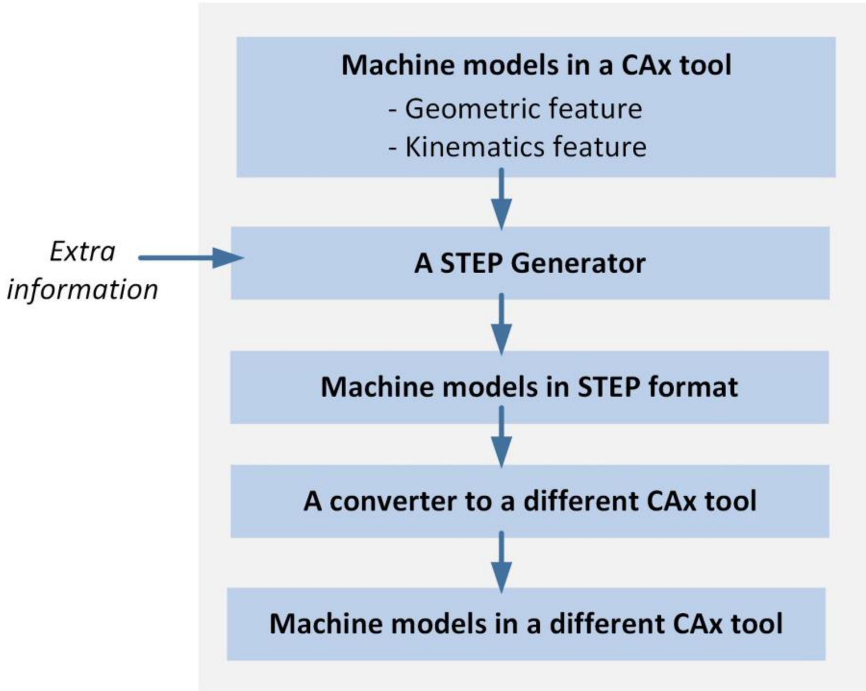

Figure 14. The general approach for creating a complete machine model in STEP format with both geometric and kinematics information

A case study was carried out, to exemplify and evaluate the applicability of the general approach that has been developed. How the application of this general approach appears in Figure 15. The case study involved a machine model that had been developed in the PTC Creo CAD software. The geometric information may be exported automatically to STEP AP 242 format using a feature in PTC Creo. The kinematics information will be exported from the machine model, supported by of J-Link. The two data sets are combined in a *STEP generator*, supported by JSDAI in translating both data sets into one complete representation of a machine model. The following sections give a detailed explanation of the individual steps in conducting the case study involving a machine model in PTC Creo.

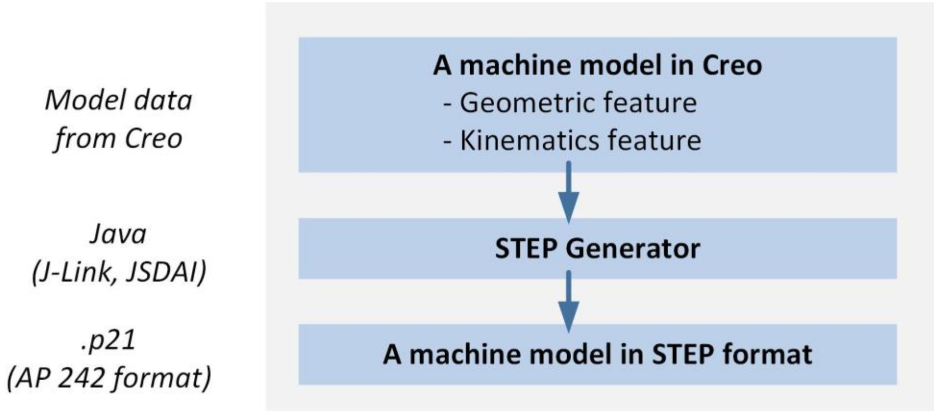

Figure 15. The case study approach: integrating a Creo machine model's kinematics and geometric information in STEP AP242

The machine model represents a five-axis Hurco CNC machine tool (called VM10UI) and was developed in PTC's CAD environment, Creo Parametric professional version 6. The machine model consists of a spindle and a Y-slide representing the machine table. The machine table may move in both x and y axes, and rotate to adjust the angle of the part being machined in relation to the spindle head. Figure 16a provides an overview of what the machine models look like in PTC Creo. Figure 16b is a close-up of the spindle head with kinematics information (in the tree structure to the left), and a definition of how assemblies and parts of the machine model relate to each other, thus determining how they may move. Each component in the tree structure in Figures 16a and 16b has a breakdown structure containing more information for the machine model. This includes information on the kinematics, defining either the rotational the translational movement in the x and y axes. Kinematics data in the Hurco Machine are defined as constraints.

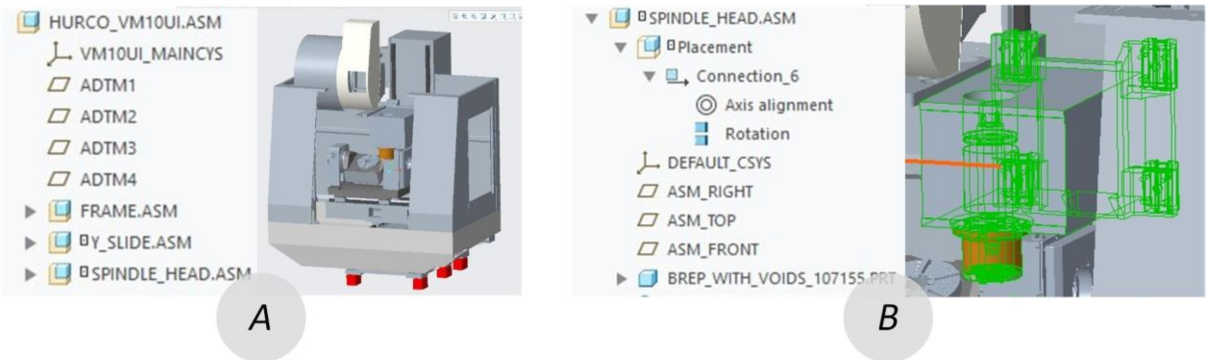

Figure 16. (a) The Hurco machine tool model in Creo Parametric, and (b) a view of the spindle of the machine and its tree structure

The *STEP Generator* was developed in a Java-based environment and, in this case, Eclipse was used. JSDAI is open-source and provides a plug-in that is compatible with Eclipse. The *STEP generator* that was developed used an iterative process to evaluate the characteristics of the kinematics information and then add them accordingly to the STEP file. JSDAI may manipulate and define data by rea-and-write access, according to the EXPRESS language used in STEP. This was used to access the geometric data exported to a STEP file and for writing kinematics data to the STEP file. This was the process used in the *STEP generator* and for creating a complete STEP model according to the AP242 EXPRESS model. An example of what the complete STEP file (.stp file) looks like once generated by the *STEP generator* may be seen in Figure 17.

```
FILE_SCHEMA(('IDA_STEP_AIM_SCHEMA'));
ENDSEC;
DATA;
#1=APPLICATION_CONTEXT('CONFIGURATION MANAGEMENT');
#2=APPLICATION_PROTOCOL_DEFINITION('INTERNATIONAL STAND
     2019,#1);
#3=MECHANICAL_CONTEXT('AP242_MANAGED_MODEL_BASED',#1,'M
#4=PRODUCT('TestID','TestName','TestDescription',(#3));
#5=KINEMATIC_LINK('33233');
```

Figure 17. An example of a complete STEP file (.stp file) generated by the *STEP generator*

4.3 DIGITAL TWIN FOR SMART MANUFACTURING

4.3.1 Definition of Digital Twin from a Practitioner's Perspective

The digital twin has been defined as a "digital informational construct of a physical system as an entity on its own" (Grieves and Vickers, 2017). There has been major hype around this concept from academia, industry, and standardization bodies. Despite this, there are still no real-world examples of digital twins in manufacturing. The slow adoption of the concept may be due to confusion about (1) what a digital twin actually is, (2) what it should include, and (3) where it should be implemented first. Other reasons include the need to collect, analyze, communicate, simulate, and integrate data in real-time. Most companies, especially SMEs, possess neither the resources nor the expertise to address these needs and build digital twins. To decrease the gap between the idea and concept of a digital twin and the manufacturing industry's understanding of it, an investigation was conducted into what a digital twin for SM means for practitioners. Five manufacturers, representing SMEs and large enterprises in different industries, plus one trade organization were interviewed. The interviewees are summarized in Table 12, with CC standing for "case company", and SC for "supply chain" they belong to. Their companies' size is also indicated; small, medium or, large.

Table 12. Summary of participating case companies

CC	SC	Industry	Size
A	1	Heavy vehicles	L
B		Forging of steel	M
C		Mechanical workshop	S
D	2	Automotive	M
E		Customizing steel products	S
F		Trade organization for suppliers in the automotive industry	

Supply Chain 1 includes Companies A, B, and C from the heavy-vehicle segment. Company A is the largest in this chain, and a customer to Companies B and C. Company A designs and manufacturers highly customized forklift trucks, with the most customized part of the forklift being the forks. This is, therefore, the product being followed in this chain, with Company B manufacturing them and company C delivering fork components. Companies B and C have both flexible production systems and Company C is deemed a mechanical workshop, able to manufacture one-off products according to customer demand. All companies in this supply chain have an ERP system in place, but there are information silos between the actors, and the order-related information is shared either digitally (by email) from Company A to B or, further down the chain, semi-automatically or by email. Upstream information in this supply chain is not digital and takes place by phone, fax, or email.

Supply Chain 2 involves Companies D and E. Company D mainly delivers products to Original Equipment Manufacturers (OEMs) in the automotive segment. Company E is an supplier to Company D but also has a broader customer base outside the automotive sector. Company E supplies customized steel products made from steel coil producers all over the world. Company D manufactures automotive products, using such processes as pressing, welding, painting, and some assembly. Much of the information exchange in this chain is done according to the EDI standard. This is a commonly used in automotive standard and is often the standard enforced by customers (OEMs) to suppliers on lower tiers. Both companies also use the Monitor ERP system.

As a technology, EDI was already in the business domain before the days of the Internet. It is currently also present in a Web environment called EDI-web, and may be used as a legacy system integrated into more up-to-date information systems (van der Aalst, 1999; Medjahed et al., 2003; Witte, Grünhagen, and Clarke, 2003). EDI has had a strong impact on supply chains and their efficiency, as it improves communication between customers, suppliers, business partners, and organizations. This was particularly so in the time before the Internet (Evans, Naim, and Towill, 1993). With EDI, it was possible to send large volumes of information at greater speed than by hard copy or analog format. It also reduces costs, delays, and errors (Abernathy et al., 2000). Because EDI has reduced the time involved in sending and sharing information, it has enabled companies to make faster decisions and bring down waiting times (Mason-Jones and Towill, 1997).

A *trade organization for suppliers in the automotive industry* was also interviewed. Many of its member companies are SMEs in the Swedish automotive market. This trade organization offers a broader view of the manufacturer’s perspective and needs in terms of digitalization, plus their current status and general direction. Due to its position and general understanding of the situation, this organization is also actively involved in research programs.

The interviews with these six interviewees are summarized in Tables 13 and 14. Each table includes the questions asked and the answers given by each interviewee. Table 13 investigates the following: 1) how the interviewees define “digital twin” in their own words, 2) the technologies involved in building a digital twin, 3) whether they interviewees believe that using standards supports building digital twins, 4) the manufacturing system lifecycles in which digital twins are most applicable, and 5) what their next steps would be in implementing a digital twin. Table 14 then investigates the benefits and challenges the interviewees can identify for digital twins in their organization, as well as more broadly for their industry.

Table 13. The digital twin concept

In your opinion, what is a digital twin?	
A	Building the factory digitally, which creates a digital copy that describes the organization and can be used for simulations.
B	A computerized 3D copy of a product or a production system or equipment.
C	A digital copy of a machine for simulating tool wear for when it occurs and how it occurs.
D	A CAD model that can be shared.
E	To build your factory virtually that will allow you to plan well before implementing it.
F	It is a digital copy of something that exists in reality, it could be a production system or a product.
What do you think of the key technologies required for the digital twin implementations?	
A	Sensors and actuators for sensing the reality and copying it to the digital world.
B	3D laser scanning to create a virtual representation, software to handle data from equipment and an analysis tool.
C	Do not know.
D	CAD and tools for building a virtual representation of a production system.
E	Software to handle the digital twin.
F	Computing power, since it will be required to handle massive amount of data. Good quality of the data that will be input to the digital twin.
What do you think of the standards that could support the digital twin implementations?	
A	It can support, since it can give insights of what is already known and existing solutions. The alternative is that everyone works on their own solution. Standards can make it more aligned and increase integration between organizations.
B	Yes, it will give a starting point.
C	Standards are mainly used when it is required by a customer, e.g., for quality control.
D	Yes, but normally standards are requirements that we need to comply with based on customers' needs.
E	Not easy to answer and we will need to make a unique implementation of it. Standards are mainly used for quality today.
F	Yes, standards could be used much more.
If applied, which of the lifecycle stage (i.e., product design, production, maintenance, etc.) you care the most?	
A	Production, to simulate flows and specially to simulate it in advance. To utilize how we are already working today to come up with how we will do it in the future. We are currently working a lot on design and material flows. Solutions in one factory could be transferred to other factories as well.
B	Production, to simulate different scenarios; maintenance, to some extent, and design, to modify products.
C	Maintenance, including both production equipment and infrastructure such as ventilation.
D	Product, in pre-production stage.
E	Production and maintenance, an important aspect is the production flows and how that can become more efficient. Maintenance does not have a more strategic plan.
F	It has potential to be important for all three stages and it should probably be investigated more. But maintenance will probably be the most important stage and artificial intelligence (AI) is more important for production.

Table 14. Benefits and challenges involved with digital twins

What benefits do you see with digital twins – for your company?	
A	The digital world makes it possible to simulate, improve, and change in a positive manner. It is a way of documenting that can be utilized in new projects. In this way, the need of physical prototypes can be decreased.
B	For modifying a product in the pre-production phase.
C	Predictive maintenance, but there is much more.
D	It is always good to have a digital representation because it is precise and easily accessible.
E	Simulate and plan flows in order to see new opportunities. The better our flows become, the more effective we become. Also, it is useful for planning maintenance.
F	The benefit is that you can simulate and test things out without interrupting in the real production system. However, it will require a business model for it.
What benefits do you see with digital twins – in general for manufacturing industry?	
A	An opportunity is for different functions in an organization that might spread geographically can meet digitally. Also, to try out new ideas before implementing it in reality.
B	Simulate and test different scenarios of both product and production digitally before going live, it is useful for multiple industries and companies.
C	Simulate different scenarios that can improve your production settings. It will help save time and cost.
D	For product information and in the context of cost optimization, you can evaluate the design in advance and give suggestions to the customer easier and earlier. Better repetitive in processes and material efficiency.
E	You can see more and view it with a holistic view. You will receive a good overview.
F	Same as for previous question, but the automotive industry has small marginal, which means that they might be hesitant for new investments. Also, they are big and do not embrace new changes easily.
What challenges or obstacles do you see for digital twin implementations – for your company?	
A	Competence, we do not really have it internally. It may be more costly if we would use a service to develop a digital twin.
B	Resources and general IT related knowledge.
C	Costs involved.
D	No challenges or obstacles.
E	To sell the idea internally, but if it can be demonstrated how it can impact profit, it will be normally positive.
F	Competence, time, and money.
What challenges or obstacles do you see for digital twin implementations – in general for manufacturing industry?	
A	Same as for our company and organizations, you have to be willing to learn and gain new knowledge.
B	Cost and other practical matters.
C	Cost.
D	No challenges or obstacles, there are only opportunities.
E	Cost, the automotive industry has low marginal and can therefore not easily commit big investments and changes, and the same as for previous question, i.e., to sell the idea internally.
F	Same as previous question and the technical prerequisites exist. However, the rollout of 5G is going slow in Europe.

4.3.2 Vision for Digital Twins in Manufacturing Supply Chains

In a supply-chain context, digital twins should be used to leverage monitoring of the business and logistical levels. This may help identify systems or areas in the supply chain that need more attention, thus motivating deployment of a digital twin at the lower levels in the ISA 95 pyramid to provide more visibility in the focus area. This way of using horizontally and vertically integrated digital twins may provide more flexibility and agility in focusing efforts on what is the most critical aspect at that moment. The vision for a digital twin's role was defined based on insights from the interviews in Section, *4.3.1*, and appears in Tables 15 and 16. Table 15 covers "use cases for digital twins in supply chains", and Table 16 "minimum requirements for digital twins."

Table 15. The role of digital twins in supply chains: use cases for digital twins in supply chains

	Description
Use cases for digital twins in supply chains	
Supply-Chain Illumination	• Support for visibility and traceability across supply-chain tiers. • Trust in supply chains requires information and understanding of where components are coming from. • Traditional tools for tracking and monitoring supply chains take too much time and are too complicated to mitigate risks. • Digital twin in the combination of traditional traceability tools can support rapid visibility in supply flows.
Mitigating Disruptions	• Due to ripple effects in supply chains, small disruptions occurring at lower tiers in a supply chain can cause significant disruptions in the higher tiers. • To be able to monitor disruptions is therefore crucial to support the output of the supply chain. • Digital twins leveraged in a supply chain can support monitoring at an early stage risk of potential disruptions.
Causal Diagnostics	• Beyond representing the physical world in real-time and predicting potential outcome, digital twins can also be used for diagnostics • This can be achieved by modeling supply flows to identify causes for an outcome to learn for the future, either by mitigating or supporting a specific outcome • Modeling can then involve both the case of what is termed as a positive and a negative outcome in order to build more knowledge across the supply chain
Security	• Supply chains involving multiple actors always face the risk of attack from external sources. • Digital twins can assist supply chains in assuring trust between actors and traceability of components exchanged in the supply chain as well in ensuring delivery of components.

Table 16. The role of digital twins in supply chains: minimum requirements for digital twins in a supply chain

	Description
Minimum requirements for digital twins in a supply chain	
Trust	• Trust is key in supply chains and can be created by the support of digital twins. • This in term requires the supply chain to be trusted that can be built by ensuring authentication, authorization, and traceability (Hedberg, Krima, and Camelio, 2019). – Authentication: to determine what a digital twin has been defined to be. – Authorization: permissions a digital twin is granted from a trusted source. – Traceability: keeping a history of a digital twin and providing understanding decision taken from the use of a digital twin.
Digital Thread	• Digital threads link together data for sensing and monitoring data and it needs to be in place for the creation of digital twins. • For modeling the system of interest effectively is digital threads necessary and in supply chains does it involve numerous nodes that the information should flow between.
Interfaces	• Connecting nodes that the information flows between, i.e., digital threads, will imply a need for interfaces between nodes to support the connection in a supply chain. • Developing standard interfaces, for example, common APIs, can speed up the deployment of digital twins. This because it will reduce the amount of needed specialized solutions and time involved in creating interfaces to support the connection between nodes.

5

ANSWERING THE RQs

RQ1) *How do manufacturing system lifecycle decisions influence the requirements of data collection towards interoperability?*

For this question, the design, operations, and maintenance manufacturing system lifecycles were investigated. In some of the studies, the actual data collection and analysis was supported by digital technologies, e.g., 3D laser scanning and 5G. This was one basis for evaluating how data may be used for decision-making. Other studies were more evaluation-oriented, based on interviews aimed at understanding the practitioner's view of a new digital concept (digital twins), and how it may support a manufacturing organization in its decision-making. The results provided insights to help answer what requirements are most important to the different manufacturing systems' lifecycle decisions.

In **design**, 3D laser scanning may collect spatial data on a factory and represent it in a virtual environment. This supported the design of a 5G network (a connectivity solution) for the factory before installation. Having connected production equipment and personnel also allowed the actual cycle time to be collected and reported, thus providing more insights into how the designed system actually behaves. This may support continuous improvements to the production system, with more accurate feedback of the system as-is and how it behaves in reality. Digital twins create a digital copy of the production system. This was deemed a valuable support in analyzing current and potential material flows. One of the key benefits is having a representation in a virtual environment that can be used to simulate and test a production system in different potential scenarios. It is also useful in the pre-production stage when designing the product and for use as a tool to communicate with suppliers. In the long-run this also impacts production. The case of virtual representation of machine tool systems also emphasized the importance of an accurate representation in making fact-based decisions. Indeed, this was one of the motivators of this study; developing a solution that could exchange complete representations of machine tool models with a high degree of accuracy, thus increasing information reuse and avoiding time-consuming reworks. Data in the design phase needs to be more accurate and representative of what is being analyzed. The design phase is where the real potential lies.

In **operations** and when running production, data availability is an important part of in supporting operators in taking proactive actions at the right time. Given more data, operators will have a better understanding of what is happening, and why. The mobile units used as a data presentation tool also supported the operators in becoming more flexible and mobile, as well as being able to make decisions wherever they may be in the factory. In the operations phase, data speed is vital in supporting decision-making that will have short-term impact. This relates to the velocity of big data; its ability to handle and present data rapidly. Digital twins are also important to operations in the same ways as for design. They make it possible to simulate and test different options or even gain a better understanding of the current state of the production system and thus to monitor and control it. Another aspect provided by digital twins in supply chains is traceability of products and components, with the opportunity to better monitor disruptions. Data requirements in operations relate to the timeliness and speed of data; having data, available when needed so that the required action may be taken.

In production system **maintenance**, the digital twin was deemed helpful in system diagnostic; understanding *why* something is happening. Modeling supply chains allows the causes of an outcome to be identified, thus supporting future lessons on how to operate the system. It may be used to plan production system maintenance, including such infrastructure as ventilation needed for running production. It also provides a strategic plan for how to maintain the production system and ensure the desired availability. In the study of 5G connectivity, in which more data on production equipment were collected, collecting vibration data might indicate changes occurring. Changes in vibration data are a good indication of what is happening and what the potential problems are. This helps the organization to act. It was observed that it can help there to be fewer unplanned stops due to machining errors. Historical data may support analysis and assist with learning from the past. Maintenance involves greater requirements for large data sets, plus aggregated historical data that may be used for analysis and learning for the future. It is important to determine the root cause of problems.

Another aspect of data identified as important to all lifecycles in a manufacturing system was the volume of data. Having a lot of data is an important driver of more data-driven decision-making and means having the right data available at the right time. When data are not presented in a way that can support the decision-maker, they do not fulfill their purpose as decision support. Thus, it is important to involve the subject-matter expert in developing new decision support through technology. It has been stated earlier that digital twins may support traceability and monitoring of disruptions; these are important aspects in building trust in a supply chain.

RQ2) *What makes interoperability standardization applicable to sharing data in a manufacturing system's lifecycle?*

Standards and interoperability standards are available to support the digital transformation that manufacturing is facing. Standardization bodies and industry are active in supporting standardization development, so the lack of supportive standards is not the issue here. Rather, it is a question of how they are implemented and how they are used, or not used. For interoperability standards, the question was what makes them applicable to sharing data in a manufacturing system lifecycle. The standards investigated in this research were developed by standardization bodies (ISO 23247 "Digital Twin Framework for Manufacturing" and ISO103030 STEP) and industry (OPC UA).

The case study (involving a complete machine tool model defined in a piece of CAD software and then translated to the neutral ISO standard STEP), revealed that there is already the functionality to translate geometrical data to STEP, but that this is not so for kinematics. Kinematics data are more complex compared to geometrical data. However, the case study demonstrated the possibility of extracting both data-sets from the machine tool model in a proprietary format and then translating it to a neutral one. Thus, the applicability of this interoperability standard is limited by the willingness and interest of software and technology providers in supporting the standard and integrating it into features that make information reuse easier for the end-user. The current situation is that many lower-tier suppliers need multiple pieces of software to comply with OEMs and be able to use their models. Another opportunity for manufacturers would be virtual simulating and testing new production equipment, if it could be converted to a neutral format.

Another example of an interoperability standard that applies to the exchange of order-related information in a supply chain is EDI. EDI has been around for some time, and in the cases examined, it was apparent EDI has become the *de-facto* standard because an OEM uses it and thus enforces its use by first-tier suppliers. They, in turn, enforce or suggest using EDI in communications with their suppliers. This makes information exchange digital and supports the exchange of information between actors in a neutral format. However, this is also something that is determines by the larger players, so suppliers need to comply.

Another aspect that would make interoperability standards more applicable is considering the use cases. This involves considering who will use the standard and how. This was investigated in one of the studies (how the “Digital twin Framework for Manufacturing” and digital twins concept is viewed from the practitioner’s perspective). Collecting and analyzing the practitioner’s perspective fosters a better understanding of how the technology and concept might be made useful to the end-user. This study also discovered that standards are considered a tool to support actors in sharing best practices and providing insights into how to approach a new area. However, many of the respondents mentioned that they mostly use standards when they have to. Examples include a quality standard that must be fulfilled because it is required by the customer.

The last insight to this question was gained from the results of the case involving a 5G network. OPC UA was the protocol used to transferring data, alongside the use of TCP and a Linux-based platform. OPC UA has more or less become standard now, for communicating and extracting data from PLCs. 5G networks that are part of the infrastructure in daily use are governed by standardization bodies, e.g., 3GPP. Thus, a technology crucial to infrastructure needs to be agreed upon, plus standards to regulate interoperability and how other functionalities should be developed for infrastructure.

6

DISCUSSION

The discussion is divided into the sections relating to manufacturing system lifecycles, data, interoperability, vision, quality of research, interaction with stakeholders in the research, and contribution to a sustainable industry.

6.1 MANUFACTURING SYSTEM LIFECYCLES

A manufacturing system goes through various phases during its lifetime and the different phases are becoming more and more interlinked. A new or modified system design is not infrequently developed concurrently with the existing production system. This thesis has investigated data collection to identify decision support to aid decision-makers. The research examined whether data collection requirements differ depending on which manufacturing system lifecycle is the subject of decision-making. The lifecycle phases investigated: were design, operations, and maintenance. These represent different stages in a manufacturing system and involve different activities. Design focusing on finding a layout and solution to support production, operations in which the actual production is taking place (focusing on achieving high levels of productivity), and maintenance that ensures the system is available for production and avoids breakdowns. All three lifecycle phases are important to the success of the manufacturing system and in reaching its targets.

As will be further elaborated in the next section, *6.2 Data*, the results showed that the manufacturing system lifecycle phase does impact data collection and data requirements. Design requires accuracy and realistic representation, operations need speed of data and knowledge of what is happening, while maintenance needs large volumes of historical data to conduct root cause analysis and plan proactively to ensure manufacturing system availability. Some requirements were more general for all phases, with large data volumes and ensuring that data fit for purpose and provided on time.

As stated, all three phases in a manufacturing system are important to the success of a manufacturing system and in reaching the intended production targets. Comparing the three phases and their progress in using more data for decision-making, there is a general tendency to focus on how more data may be collected and used in the maintenance stage. Ensuring availability is an important target and thus drives the focus on finding new ways to plan and take proactive action. In operations, many benefits were identified that may allow personnel to be more flexible and mobile, yet still have the right information to make the right decisions. However, it was observed that manufacturers largely base their decision-making on their experiences and intuition. In designing manufacturing systems, the use of digital representation is increasingly adopted, in a similar fashion to the development of digital product representation. However, most companies are still not completely there. Reasons may include the time-intensive activities required to keep a digital representation alive, and being accurate and representative when productions system are prone to frequent change. All three manufacturing lifecycle stages are important. Thus, to ensure a development toward making decisions more data-oriented, an understanding and specification is needed outlining the data collection requirements of each phase. Processes and decision-making in design, operations, and maintenance could become more democratized, with various roles in the manufacturing system collaborating on the same data and digital representation.

6.2 DATA

The recent changes in technological development, with devices becoming smaller but at the same time more powerful and affordable to use, is changing industry and society. The opportunities provided by technology mean that there is now the prospect of thoroughly re-thinking how things are done. However, this depends on an appropriate use of technology to resolve the current issues being struggled with. So far, there has mostly been a technology push and an attempt to find a problem to a solution. However, if a different stance is taken, starting with an investigation of how production processes and operations are done today (and involving domain experts in the production organization), then there is the opportunity to identify real production problems that might be solved by technical solutions.

The technology shift faced by manufacturing, is commonly called the Fourth Industrial Revolution. This shift emphasizes the opportunities of digital technologies, envisioning a future production system in which a vast amount of data informs decision-makers about most aspects of the manufacturing system throughout its lifecycle. For this to happen, I believe that the problem needs to be identified, plus the data requirements set by the decisions taken. The vast amount of data already available in some sectors is called *big data*. One of the first definitions of big data (Laney, 2001) mentions the volume, velocity, and variety of data. Volume refers to the amount of data available, velocity the speed at which data may be retrieved and acted upon, and variety the different sources of data used.

One of the research questions posed in this research was to investigate whether data requirements differ depending on the manufacturing system lifecycle decision. Since the vision of the thesis is to make future manufacturing systems more fact-based in their decision-making, there is a need to investigate how data should be collected and analyzed so that they address real production problems and are presented in a way that better supports manufacturing. Based on the results, it may be noted that the three aspects of big data play varying importance depending on the manufacturing system lifecycle decision in question. In the **design** phase, the emphasis is on the accuracy of data and for decision-makers to be presented with a realistic representation of their production system. This phase has a considerable lead time and is not a matter of presenting information in real-time. Thus, data speed is not currently crucial to this phase. However, a variety of data sources may be valuable in providing a complete picture as possible and supplying accuracy. In **operations** and running production, speed and ability to act are normally crucial. When a sudden event occurs, operators, material planners, or other decision-makers closely related to the production processes, want to ensure the required actions do not risk production interruptions that might cause commitments to customers to go unmet and available productivity in a production system to go unused. In operations, the knowledge that something has happened may be more crucial than the root cause of the event or error. This speaks in favor of speed over richness and quality of data. The last lifecycle discussed in this thesis is **maintenance**. Traditional maintenance has mainly involved serving manufacturing and production processes when problems occur, and ensuring that the equipment is available as soon as possible again after it breaks down. The new opportunities provided by technology are changing how maintenance may be carried out. It may change from being reactive to proactive and, once historical data has been evaluated, even predict system behavior. From an application perspective, this requires richness and quality of data, if it is to help finding the root causes of problems. Ideally, this means analyzing historical data, whit the amount of data being crucial in finding the root cause. The volume aspect was also deemed interesting in all lifecycles of a manufacturing system.

6.3 INTEROPERABILITY

New technologies can support the collection and analysis of data, which means that more data (meaning in both volume and variant) may be made available. It has been stated that manufacturing is a sector that possesses the largest volume of aggregated data, but which is simultaneously the most dispersed sector when it comes to data because organizations (or even functions within them) create information silos where information is not shared (Manyika et al., 2011). There are many reasons for this, one of which is interoperability. Systems are not interoperable *per* se, but interoperability standards exist to help overcome this problem. However, even though the interoperability standards exist, they are not fully utilized. The second question of this thesis approached this existing challenge by evaluating what makes interoperability standards applicable.

One of the studies in this thesis investigated the practitioner's perspective on digital twins in a smart manufacturing perspective, and asked the question *"What do you think of the standards that could support digital twin implementations?"* One of the interviewees answered, *"It gives support by providing insights into what is already known and about existing solutions. The alternative everyone working on their own solution. Standards can make it more aligned and increase integration between organizations."*

Another stated that "*Yes, standards could be used much more.*" So, according to the users, there is a need and interest in applying standards, with the alternative being everyone creating their own solution. So, why are they not more used in in overcoming the existing information barriers in manufacturing? Comments from two other interviewees were, "*Standards are mainly used as required by a customer, say, for quality control*" and "*...standards are normally requirements that we need to comply with based on customers' needs.*" Thus, besides the technical challenges of overcoming information silos relating to existing information systems that are not interoperable, there are other reasons why interoperability standards are used or not used.

Customer requirement and push was also a finding in **Project B**, in which a supply chain for companies active in the automotive industry complied with the EDI standard for information exchange between actors. This information mainly relates to order information and was standardized to provide information exchange in a supply chain. EDI is a standard used by OEMs and enforced as the way to communicate with tier 1 customers. They, in turn, enforce this further down the supply chain. In this case, it was demonstrated that the supplier must adapt to the much larger actor in the way it exchanges information, thereby creating interoperability. Another example investigated in this thesis involved the exchange of machine model data. Data and information built into machine models are normally rich and used in evaluating an operation sequence, investment in a new machine, a new tool or fixture, and so on. Even though data richness is inbuilt in these models, they may seldom be translated into a neutral format. Again, this may be a problem for the supplier. Complying with all their customers and handling their products means having all variants of virtual tools (CAx systems). This is a costly solution in terms of both software and resources, as they must be able to handle numerous systems.

For the case of translating machine model data into a standard format, this feature is already available in most CAD software, for automatic creation of a STEP file containing the geometrical information. However, the kinematics information on a machine model is lost in this step. This is valuable information in evaluating, say, a production process or sequence. The kinematics information is more complex to translate to the neutral format compared to geometrical information, but the efforts in **Project C** showed that it was not impossible. This is a real industrial problem to which industry is seeking a solution, so why has it not yet been implemented by the technology providers? Aside from the complexity of kinematics information, one reason is believed to be the lock-in effects created by technology providers. As mentioned in *Ch.2 Frame of Reference*, implementing a standard should be done identically to ensure its complete integration with other implementations. However, standards are seldom implemented identically in every case because, during implementation they undergo customization and extension. This is because suppliers want to create a unique selling point for their solution and gain a competitive advantage (Lewis et al., 2008). This strengthens the point about the lock-in effects created by technology providers and why this has still not been implemented for machine model data.

Another side to interoperability standards comes from **Project A**, in which 5G communication was used to connect machines and humans. 5G communication, the fifth generation of telecommunications, is regulated by the standardization body 3GPP and must align with the relevant directives. It is a crucial part of the infrastructure and cannot, therefore, be developed in isolation by various technology developers.

In one of the studies in this thesis, the practitioner's perspective was investigated to understand how the digital twin concept is viewed and understood by industry. This study was driven by the fact that there is an ISO standard under development, "Digital Twin Framework for Manufacturing," aimed at providing guidelines and insights. This concept has attracted much attention from both the research community and among technology providers, but there are few available real-world examples. As stated in **Paper 5** the real value of digital twins will be seen once they are integrated into supply chains. Compared to infrastructure standards, as for 5G, or quality standards exemplified by the interviewees as a standard they needed to comply with to fulfill customer requirements, a digital twin standard is not a standard that companies will have to comply with or use. It may provide guidelines and best-practice to help companies avoid having to re-invent the same solution over and over again, but the risk is that it will not support manufacturing companies in taking the next step on the digital transformation journey. Therefore, use cases of how the standard may be used are important. Moreover, perspectives on how the standard may help manufacturing companies is important in increasing the usability of the standard and its value to manufacturing. Otherwise, there may be a risk of it also contributing to the technology push; a solution looking for a problem to solve.

Automation of manufacturing, the Third Industrial Revolution, created individual systems and information silos in which interoperability was missing. At this point, on the verge of the Fourth Industrial Revolution, the expectation is that massive amounts of data should flow from production processes and inform decision-makers how to make better decisions. But, if we still have interoperability issues and do not overcome these information silos, the transition will be more difficult. We need standards that support interoperability and solutions to make existing manufacturing systems interoperable, with true integration and avoiding lock-in effects.

6.4 VISION

My vision is for future manufacturing organizations to be driven by fact-based decision support based on data, rather than relying mainly on intuition and experience.

The vision I have stated for a future manufacturing organization has already become a reality for some industries today. From the literature presented in this thesis, this is also a vision I share with other scholars, standardization bodies, and technology providers. The digital twin concept, for example, relies on accessing production system data in real-time. But how close are today's manufacturing organizations to achieving this vision, and what is their perspective?

The studies conducted in this thesis identified that decision-makers (including operators, material planners, production engineers, and so on), are making a decision based mainly on intuition and experience. In the case of the connected machine and human in **Project A**, the focus group comprising decision-makers with various roles in production stated that, most of the time, they did rely on intuition and experience when making a decision. However, they did acknowledge the importance and opportunity of becoming more data-driven and oriented. Within maintenance, this was something they were already applying to some degree, via manual measures (manual data collection). They also observed that the opportunities afforded by digital tools to collect data and information would expand the opportunities to analyze historical data and correlate data sources; that has not previously been done. Another interesting aspect brought up in this project was the opportunity to change the way of working afforded by new digital technologies. With data via mobile devices informing operators of required actions in a machine, operators may be kept informed wherever they are situated. This supports the mobility of personnel, in line with the trend of not having responsibility for just one machine as an operator.

In **Project B**, practitioners from manufacturing industries were interviewed. They represented various companies, ranging from large to SMEs and came from different industries. One of the interviewees was from a trade organization representing hundreds of SME suppliers in the automotive sector. When investigating their digitalization strategy, it was found that few of them had any clearly stated one within their organization. In regard to the use of smart manufacturing technologies they were not using smart sensors, with most using local servers for their databases, and some using a cloud. Regarding models, about half of them stated that they used the to represent their product and/or production equipment, and half of them did not. However, most of them acknowledged the possibilities and opportunities of digital technologies. For example, one of them stated, *"The digital world makes it possible to simulate, improve, and change positively. It is a way of documenting that can be used in new projects. In this way, the need for physical prototypes may be decreased."* Challenges expressed by the interviewees, mainly on the topic of building digital twins in their organization, involved competence, costs, and time required. Competence was something many of them stressed that they lack, while cost and time required was a matter of convincing management and being able to demonstrate the benefits and profit gains to be achieved by using digital technologies and creating specific digital twins.

Most aspects listed here favored my stated vision for manufacturing organizations, but with some challenges involved. Competence was an aspect raised as a challenge to moving to a more digital future in which decision-making is data-driven. The interesting question here is what the future workforce in manufacturing will look like and what skills will be required to support the digital transformation. Will it require new ways of training, a new education system, and so on? And will this become an obstacle to achieving my vision? Another possible challenge (or, at least, consideration) that needs to be made in manufacturing concerns security and how production systems data is handled. This is particularly pertinent, as more equipment and assets are becoming connected and, as discussed in this thesis, there is a need for more interoperability so that data and information may be easily shared between functions and organizations.

I consider my vision to be on the right trajectory, given that most other industries are heading in this direction and based on the findings presented in this thesis. Manufacturing organizations are not yet there, but this research has contributed insights into how it may support the decision-maker and become valuable for the manufacturing organization. This is one step in the right direction. It should be remembered that this transformation needs to be driven from the perspective of which problem to solve and inform. There should be a technology pull, a point at which a collaboration is needed between manufacturing, academia, technology providers, and standardization. The applied-oriented research informs academia, standardization bodies, and technology providers of what actual problems need to be solved and supported by digital technologies.

6.5 QUALITY OF RESEARCH

This thesis is grounded in work conducted across three research projects, with the results documented and published in the four peer-reviewed papers and one manuscript under revision appended to the thesis. The purpose of a research method is to be transparent as to how its results were collected and to enable the repeatability of studies. This allows other researchers to replicate or perform a similar study with comparable results. To ensure this, a major emphasis in this thesis and its appended papers has been to explain the rationale behind a given study, the motivation for it needing exploration, and the details of its implementation. Interview questions were included where applicable and, for the experiment, the technical development and software were explained in detail, to give insights into how this study was conducted.

The philosophical standpoint of the research was to address a real-world problem, an achievement facilitated by research projects. For the two research questions, three research projects provided results that helped to answer the questions. The research approach was a mixed-methods one, that has the benefit of mixing qualitative and quantitative data collection methods. Combining these allowed the benefits of both to be gained, whilst complementing each other's weaknesses and thereby better serving the purpose of answering the two research questions. Numerous data collection methods from quantitative and qualitative methods were used such as a literature study, interviews, focus-group interviews, experiments involving 5G connectivity, the development of a technical solution to enable data exchange between software, and so on. Combining numerous data collection method, served to answer the research questions, aided by the triangulation of data collection methods.

The results of the thesis were obtained from research projects, involving the active participation of manufacturing companies. This served the purpose of addressing real-world problems and ensuring the impact and benefits of the research to industry. The type of manufacturing organizations participating in the projects were diverse, both in terms of the organizational size (from SMEs to large enterprises) and the industries in which they are active. The range of manufacturing organizations participating in these projects provided further insights into the similarities and differences between large enterprises and SMEs in approaching the digital transformation. It thereby provided a more holistic overview of the needs of the manufacturing domain.

The research projects paid a great deal of attention to developing proofs-of-concept on how digital technologies might be used. This was to demonstrate the application of digital technologies in solving and addressing the challenges among the manufacturing organizations involved in the projects. The development of proofs-of-concept was carried out at the smart manufacturing laboratory at Chalmers University of Technology, NIST and, when possible, at the manufacturing organizations' sites in a test environment or in real production. Since the development is meant to provide a technology pull rather than a technology push, the development of proofs-of-concept was important to gain an understanding of how the technologies might be used to address real problems of manufacturing. The proofs-of-concept also involved a collaboration between research, manufacturing organizations, and technology providers. This ensured a joint understanding of the technical solution's solving of a real-world manufacturing problem. It further assures the aims of the thesis; to show manufacturing organizations how digital technologies might be used and applied to provide more fact-based decision support.

6.6 INTERACTION WITH STAKEHOLDERS IN THE RESEARCH

As explained in the introduction, *Ch. 1.7 Stakeholders*, a number of stakeholders are relevant to this research and have an interest in its results. These are manufacturing organizations, production personnel and decision-makers in manufacturing, politicians and funding agencies, standardization bodies, and academia. There was some type of interaction with most stakeholders throughout the research. Table 17 summarizes the stakeholders in this research and the type of interaction with them, or their interest in the research. As indicated, the type of stakeholder is categorized into the private and public sectors, plus academia.

Table 17. Stakeholder interaction throughout the research

Sector	Stakeholder	Interaction with stakeholders
Private sector	Manufacturing companies in discrete manufacturing, process, textile, food industry, etc.	Manufacturing organizations are important stakeholders in the research but also important contributors. The results of this thesis are grounded in research projects carried out in collaboration with manufacturing organizations. The interaction with the manufacturing industry totalled 30+ individual companies active in various manufacturing industries, such as space, automotive, textile, steel manufacturing, and bearings. However, there were also technology providers from telecommunications, IoT platforms, automation, PLM systems, and hardware such as sensors and PLC, etc.
	Production personnel and industry professionals	To understand the applicability and value of having more fact-based decision support, it was important to get the perspective of production personnel, decision-makers in manufacturing, and practitioners in general. Numerous focus-group and semi-structured interviews (about 15) were held. Another outcome of the research is a course module of 1 credit on 5G and connectivity in manufacturing targeting industry professionals and students at Master's level. So far, about 10 industrial professionals and 100 students have taken this course module.
Public sector	Politicians	Many countries have now adopted the Industry 4.0 agenda proposed by German president, Angela Merkel, as part of their own context and priorities. In the Swedish context, this topic was also raised at governmental level, and for the strategy for renewing Swedish industry, focus areas were proposed such as Industry 4.0, sustainable production, competence increase, and testbeds.
	Funding agencies	The research was funded at national level by the strategic innovation program Produktion2030, Vinnova, and NRFP (funding research in the space industry), and at international level there was EU funding from Horizon2020, and funding from the US Government.
	Standardization bodies	During the research have I acted as a member of the technical committee 280 at the Swedish Institute for Standards (SIS), and as an expert on the international mirror committee ISO Technical Committee 184 Sub-Committee 4 Joint Working Group 15, "Industrial Data." This involvement made it possible to better understand the process of standardization development. The studies in the research both applied one standard, ISO 10303 STEP, and addressed why there are still few real-world examples of digital twins, ISO 23247. Six months were also spent at NIST in the US. During the exchange, the research focused on standardization work.
Academia	Research community	The research has resulted in eleven peer-reviewed papers and one manuscript submitted (as a first or co-author) and two theses. The research has been presented at seven international research conferences. Journals and conferences were selected according to topic, relevance to the research, and opportunity to extend the network within the field.

Over and above the stakeholders mentioned in Table 17 and the type of interaction carried out, there has also been interaction with the World Economic Forum (WEF), as I have served as a fellow of the Global Future Council on Advanced Manufacturing and Production. WEF attracts many manufacturers in the global market that can demonstrate and share interesting examples of how they approach the digital transformation. Being part of this context has provided insight into, and lessons on, the ongoing discussion in this area from companies, academia, and the public sector leading the drive in this transformation.

6.7 CONTRIBUTION TO A SUSTAINABLE MANUFACTURING INDUSTRY

The manufacturing industry impacts our society, contributes to productivity, creates jobs, and ensures the supply of goods. But, it also affects the environment. New digital technologies are changing the way work is done and have the potential to impact how industry contributes to more sustainable manufacturing. This section will discuss the contribution of the research presented in the thesis to creating a sustainable manufacturing industry. The discussion is divided according to the triple bottom line of environment, social, and economic sustainability.

Environment – the vision for future research is that manufacturing organizations will become more fact-based in their decision-making instead of relying on experiences and intuition. The results presented here have mainly focused on how to improve decision support to increase productivity, flexibility, quality, etc., rather than how decision-making may affect a manufacturing organization's environmental impact. The concepts and procedures presented here are similar, however, in that they are applied to start measuring energy use, scrap rate and material use, transportation, and other factors affecting the environment. Being provided with more fact-based decision support may then provide the insights needed to make better decisions and have less of a negative impact on the environment. One application of this that was stressed in the interfaces between organizations is the traceability of materials and products, meaning the product flow and information on how it has been manufactured. Digital twin has major potential here, to provide more data and information at the interfaces between organizations when digital representations of each production unit are created.

Social – the human fear of being replaced by new technologies has been a widely discussed topic throughout the industrial revolutions and is, hence, not a new concept. For example, machines, industrial robots, and now artificial intelligence have replaced manual tasks previously carried out by humans. Thus, there is a fear that jobs will be eliminated. The results of this thesis might also be viewed from this perspective, as they propose that the intuition and experiences of human workers should be replaced by more fact-based decisions. However, that is not the intention. Rather, this work seeks to complement human intuition and experience with more data and information, representing how the actual production system and its processes are performing. It is meant to support human workers and may also support organizations in democratizing the decision-making process by enabling the same data and information in making a decision. However, new technologies will require new types of competencies: something that has been stressed by many of the SMEs taking part in the studies for this thesis. Competence increase and life-long learning will be vital in preparing the future workforce for the new manufacturing environment, in which the data and information enabled by digital technologies may inform their decision-making.

Economic – new digital technologies may change processes and the way work is carried out. The results presented in this thesis demonstrate that they may support and impact important values in manufacturing, such as productivity, flexibility, quality of products, etc. These are all important measures in economic growth and profit. So, the may be said to demonstrate positive effects on the economic aspect, contributing to greater economic sustainability. Nevertheless, one challenge that has been encountered in this research is the ability for SMEs to invest in new technologies. For large enterprises, it is largely a matter of how to motivate the investment based on traditional return on investment (ROI) calculations. From an economic perspective, it is time to change the way investment in digitalization is viewed and evaluated, as digitalization normally involves major investment in infrastructure, and the return of this is hard to calculate on a few years period. It will most probably take the manufacturing organizations several years to gain a return on their investment in digitalization and, when it starts paying off, they will be on track with the new digital transformation we are now experiencing. However, it requires manufacturing organizations to rethink investment projects and adopt new metrics to better support the digital transformation.

7

CONCLUSIONS

My vision for future manufacturing organizations is that, supported by data, they will become more fact-based in their decision-making. I can conclude that manufacturing organizations have not quite realized this vision yet, and that the use of smart manufacturing technologies is still limited. This is due to uncertainties about how new digital technologies may be used to create value, the existing challenges and obstacles involved in handling and sharing data, and the organizational challenges of change. The focus also tends to be on digital technologies rather than on how they may be put into practice to support digital transformation. These conclusions will highlight aspects to support manufacturing organizations in moving closer to my vision.

The results demonstrate that depending on the manufacturing system lifecycle decision (i.e., design, operations, and maintenance), the main findings for data requirements:

- *accuracy* in the design phase, creating a representative and accurate digital picture of a manufacturing system, including spatial and machine tool model data;
- *speed and wide variety* of data in the operations phase, providing knowledge about the condition of a resource or piece of equipment in real-time or near-real-time, and;
- identifying correlations and trends by *analyzing historical data*. In maintenance, it is crucial to plan proactively for the future and find the root cause of problems.

Some data requirements were found to be important to all manufacturing lifecycle system decisions, including the *volume* of data and having the *right data available at the right time*.

Interoperability standards may enable better information reuse, interoperability between systems and organizations, and more consistent management of information. The main findings as to what makes an interoperability standard applicable to manufacturing organizations are:

- *interest and willingness* by software providers to apply international standards and share data in a neutral format;
- *enforcement of standards* by OEMs and suppliers at the higher tiers , as to how data should be exchanged in a supply chain for creating digital information flows;
- that the relevant *manufacturing use cases* are considered when developing a standard and that SDOs should develop *guidelines and procedures* to help industry, especially SMEs, to start the implementation process, and
- actors *need to agree on standards* when it relates to infrastructure, i.e., in

telecommunication.

The aspects listed here for data requirements and making interoperability standards applicable may support manufacturing organizations in moving closer to my vision. In the studies carried out with manufacturing organizations, there was an awareness among them about needing to approach this area or to be already starting their digital transformation by becoming more fact-based in their decision-making. Future efforts will also need continued collaboration between manufacturing organizations and academia, as demonstrated in this thesis. Proofs-of-concept can demonstrate how digital technologies may support more fact-based decision-making and that the view the practitioners should be considered when developing of new technologies and standards.

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