Supply & planning in the factory of the future: The implementation framework

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Challenge the future

Supply & planning in the factory of the future: The implementation framework

by

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in partial fulfillment of the requirements for the degree of

Master of Science
in Management of Technology

at the Delft University of Technology,
to be defended publicly on Wednesday August 26 2020 at 10:00 AM.

Student number:	4600142	
Project duration:	February 3, 2020 – July 10, 2020	
Under guidance and supervision of:	Dr. A. Y. Ding,	TU Delft
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This thesis is confidential and cannot be made public until August 26, 2020.

Preface

I would like to express my gratitude to my supervisor Dr. Aaron Ding for his invaluable advice and guidance throughout my second master thesis. His expertise and patience really added to my graduate experience and this research. Weekly discussions with Aaron kept me on the right track finding the most useful information to enhance future success of the Industry's largest project: digital transformation.

Besides the weekly supervision, a special thanks goes out to Dr. Lorí Tavasszy, for his time, feedback and supervision during the core meetings. His input enabled new insights, imposed a critical look at my own work and shed light on different perspectives. With the immense knowledge and experience of Lorí and Aaron, I was able to get this thesis to the next level, hopefully helping multiple factories in their adventure towards Industry 4.0-implementation.

-For confidential reasons, I will adhere to roles, but they know who they are.- First of all, I want to thank the Human Resources (HR) manager and operations manager for expressing their confidence in me, by approving my initial idea and giving me permission to execute the thesis and its case study at the company's side. Also, their advice and comments were extremely valuable. In addition, I want to acknowledge the immeasurable support by the VP Operations, maintenance manager, supply & planning manager, and the production planner for their assistance, source of information and time. Besides these internal contacts, I am grateful for the tremendous input of the interviewees who contributed a lot of useful insights. Especially their enthusiasm about the topic is something to admire, which I will never forget.

Finally, I would like to thank my family, and Shannon in particular. You supported me the whole adventure, both in the Chemical Engineering and the Management of Technology masters. Without you, these 3 years of dedication, perseverance and setbacks would have been unbearable. You just made everything better with your continuous support. Thank you for your patience, your advice and keeping that mirror in front of me.

Rocket science itself will not shape our future, it must be applied in a rocket science way.

Davey Nijland (4600142)
Vlaardingen, July 2020

Executive summary

Recent developments in technology innovations show that huge efficiency improvements can be made in the manufacturing industry. Moreover, companies that adopt the new innovations, associated with Industry 4.0, can create a huge competitive advantage. However, these rather conservative businesses are slow adopters and usually wait for proof-of-concept before actual implementation. Since this industrial revolution, Industry 4.0, is still in its infancy, more research is required to get to full adoption. Although the industry still awaits proof-of-concepts, many different case studies have been performed, and with success! These clearly exhibit the versatility of the Industry 4.0-philosophy, making widespread adoption just a matter of time.

One of the identified reasons for this lag in adoption is the lack of clear implementation guides despite the thorough research and redundancy of technology. Due to the holistic Industry 4.0-concept, many practitioners lose sight on how and what to implement. Various researches proposed the creation of a widely applicable implementation model, but this is yet to be developed. One of the prominent issues related to creation such model is the all-encompassing nature of Industry 4.0; it includes novel innovation in supply chains, in factories, and even in the products manufactured. Since there are clear differences between these 'applications', a generic overarching model seems unreasonable considering the immense amount of variables to consider. This thesis depicts the first ever-made implementation model specifically aimed at improving raw material supply & planning in complex manufacturing companies.

Supply & planning processes are the closest connections between a manufacturers' own operations and its closest neighbours in the supply chain; i.e. suppliers and customers. Tapping into this specific field of operations enhances the utilization of Industry 4.0 both on the supply chain and manufacturing aspects. Through answering the main question, and several subquestions, relevant information is gained that enable the construction of an implementation model. The design of such implementation model includes a step-by-step approach for practitioners of manufacturing companies, and a clear description on what to consider at each step. Creation of the artefact (i.e. implementation model) happens by explaining the research question:

How can Industry 4.0 be implemented into supply and planning departments of complex manufacturing companies using an implementation framework?

By means of a design science research methodology (DSRM) the Industry 4.0 supply & planning implementation framework is designed. Through 6 pre-determined steps; (i) problem identification, (ii) objective definition, (iii) design & development, (iv) demonstration, (v) evaluation, and (vii) communication, it ensured that all relevant stages are included to construct a scientific substantiate artefact. Three of these elements in particular were considered to be main constructs of the thesis report. Through the objective definition stage, qualitative research in the form of interviews and literature review imposed what had to be included in the implementation model. In the design & development stage this information was casted into a mold, thereby being the first result to the thesis' ultimate goal. The demonstration phase was assigned to check the applicability and effectiveness of the model by putting it into practice. Altogether a significant base of information was collected, obtaining the first conceptual implementation model for Industry 4.0.

In the existing tight markets in which various manufacturers operate, the utilization of improvement technologies is high. Techniques derived from methods like Lean, Agile and Six Sigma are used on a daily basis. Because companies are familiar with the use of these models, the adoption of newer versions becomes straightforward. Consequently, the implementation model is a derivative of such method, namely the DMAIC (Define, Measure, Analyze, Improve, and Control). Since these overarching steps do not provide sufficient information for actual implementation, extra delineation is applied

through a combination of the Continuous Quality Improvement model and practitioners' experiences. Via combination of the two, a first model consisting of 11 steps (i.e. within the 5 DMAIC stages) was constructed.

The implementation model starts with goal identification, in which the companies' digital transformation (i.e. Industry 4.0-adoption) strategies are adapted to local needs. Subsequently, the business processes are investigated thoroughly. By clever modification of an existing model called RAMI (Reference Architecture Model Industrie 4.0), a standardized approach for identifying the key aspects of the business processes was obtained. Using the results of this business process modelling allows to diagnose the so-called key variables that have a considerable effect on the performance of operations. The top five of these key variables provide the focus for the execution of the consecutive steps. Data and information about these 5 variables is gathered through a process of replacing paper forms by digital forms and through connection of existing Operational Technology (OT) systems with Information Technology (IT) systems. Once all the relevant data for the five variables is obtained, a data analysis follows. Examining the inconsistencies in this data pinpoint the location where data enhancement (i.e. Industry 4.0-adoption) will significantly improve the process. Defining the performance indicators then help to know the business' existing performance and allow comparison with future results, but also help users to monitor real-time process-efficiency by means of a dashboard. According to the Key Performance Indicators (KPI's) chosen, technology introduction can finally happen. Thirteen different enabling technologies were identified during the literature research, providing practitioners a wide portfolio of options in their Industry 4.0-implementation. Shortly after implementation follows continuous monitoring according to the aforementioned KPI's. By carefully assessing the business process' performance, improvement studies can be performed and actual improvement of the system can take place. In the final stage it is evaluated whether the implementation was effective and what lessons-learned should be brought to the next technology-implementation.

To test whether the implementation model indeed fulfil its vows, a test run is performed at an agriculture fertilizer manufacturing facility that definitely classifies as a complex factory according to the definition of this thesis (i.e. large portfolio of products and raw materials). The first few stages were quite obvious in their execution, mainly because of the clear instructions given. Especially the modified RAMI model gave useful insights and abandoned the requirement of complete Business Process Mapping which is very time consuming. Various key variables were obtained using a quality team. Since the majority of data -for these key variables- was already available, it was only a minor effort to obtain the rest using either OT-IT merger or digital reporting. In the case study, the data analysis stage was the most demanding task in both time and extra investigation. After describing the KPI's related to the data analysis and describing the technology introduction stage, the real version of the case study had come to an end due to time and resource limitations. Continuous monitoring, improvement, and evaluation were further concluded through the sense of 'modelling', where providing examples and describing the expected outcomes served as enclosure of the first trial.

Although the model was designed with extra care and the input from both the literature review and the interviews were significant, some limitations still apply. It was observed that some of the stages were not definitive enough, making the actual goal of each step rather vague. As a result, some stages could take considerably more time than necessary, diminishing the model's effectiveness. Moreover, the power of the data analysis, as described before, was truly reliant on my experience in statistical and data analytics. Therefore, the current data analysis-description requires more attention to advance the usefulness of this stage regardless of the users' experience. Finally, the effectiveness and generalizability of the model were only touched upon briefly and require more in-depth investigation before claiming its novelty.

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1
Introduction

In recent years there has been a considerable shift in thinking with regard to digital transformation inside manufacturing companies. This shift is a clear consequence of rapid innovation and applying it creatively inside the manufacturing industry. As a result, companies become more flexible and also efficient in doing so. Competitive advantage awaits those who swiftly adopt their way of operations to this new digitized era. Simultaneously, a former hellion for business became the today's goldmine; data. It is this data that can significantly improve existing operations when being applied in a smart manner, creating the smart factory of the future.

Many researchers explore the realm of 'SMART' by applying the same principles on concepts like supply chain, maintenance and production in general. However, smart can even be interpreted in the widest sense of it. Indicating that particular processes, other than transportation and manufacturing, could benefit from these new smart principles as well. Consequently, businesses can improve their existing operations by applying the same digital transformation philosophy to a multitude of processes.

Reading my thesis should help you to understand the critical layers of this ambiguous concept called digital transformation. The report will outline what aspects contribute to effectiveness of successful implementation and provide an overview of all contributing conditions.

1.1. A changing industry

2012 was for most companies the first year in which they were faced to the new industrial trend; digital manufacturing (Hozdić, 2015). Due to the holistic nature and the failure of many other technologies, many companies abandoned the concept as soon as they became aware of it. As a result, only the companies that stood out, willing to take an extra risk, invested heavily into this new business opportunity. Subsequently, these firms obtained a competitive advantage in the years to come, obligating the competition to follow soon after. Nowadays many companies understand the need for such transformation, but simply do not have the competences to do so, making Industry 4.0 one of the biggest challenges lying ahead for the manufacturing industry.

1.1.1. Industry 4.0

In order to keep up with the flexible demands of today's society, a shift in the way of working for manufacturing companies is mandatory. The Third industrial revolution, also known for its programmable logic controllers (PLC's), originates from the 1960's (Hozdić, 2015). Ever since, the manufacturing industry remained quiet and only minor innovations found its way towards a more efficient way of producing, e.g. micro-processors, Genetically Modified Organisms (GMO's) for the food industry and recently, the 3D-printers. Compared to the shift from analogue to digital mailing, the internet and mobile phones, the manufacturing industry kept utterly conservative.

A new industrial revolution, industry 4.0, lies ahead and awaits it widespread introduction to the manufacturing industry. This industrial revolution is supposedly focused on the implementation of tomorrow's innovations into today's manufacturing facilities. Because the industry did not evolve as rapidly as the 'outside world', it faces a galore of burdens for full implementation (Heritage, 2019). To avoid unnecessary capital being spend, it is of upmost importance that these challenges are being addressed before actual implementation. This requires a full plan and architectural structure tailored to the factory of interest.

Several approaches to industry 4.0 are taken, with a variety of interpretations by multiple researchers. "*Integration of complex machinery and devices, with sensor and software networks, used to predict, control and improve plan business and results in society.*" (Saucedo-Martínez *et al.*, 2018) and "*The smart factory, key concept of Industry 4.0, depicts a future state of a fully connected manufacturing system, mainly operating without human force by generating, transferring, receiving and processing the necessary data to conduct all required tasks for producing all kinds of goods.*" (Osterrieder *et al.*, 2019) are just a few of the many different concepts derived by researchers. In order to describe and elaborate on the Industry 4.0 meant throughout this research, another view is defined in this report:

Industry 4.0 is the fourth manufacturing revolution that evolves by companies implementing novel technologies in a smart way to improve current operations in the realm of autonomy, efficiency and social responsibility.

Autonomous in this case refers to the applied pre-programmed smart technologies that make decisions and also perform them by assessing data without human interference. Social responsibility infer the trade-offs made by the company that opt for more social-favorable options, e.g. less energy consumption, rather than choosing for the most profitable option only. Obviously, both drivers of industry 4.0 can only be applied to some extent, depending on the current state of development in technological innovations. The industry 4.0-portfolio, according to the definition in this report, include all technologies that enable quick, autonomous and automatic processing of data and technical actions, e.g. sensors that convert physical appearance into 'digital' data, Internet of Things (IoT) architectures that manage that data, Artificial Intelligence (AI) that converts data into preferred actions, and Cyber-Physical systems that perform the operations (Belli *et al.*, 2019). This even includes the utilization of existing dull technologies by shaping them to fulfil a role within the Industry 4.0-network. The full portfolio offers various technologies that enable companies to make significant improvements in terms of efficiency and effectiveness.

Within the Industry 4.0 era, a lot of factories will alter the way of operations, because the improved efficiencies allow to increase the profit margins. Factories that currently face little efficiency, due to the increasing demand for flexibility, can be found as complex factories. Complex factories, as introduced in this report, are characterized by their large amount of different raw materials, products, and very stiff production processes that have to process this wide variety of products. These factories can experience the most powerful shifts in their way of operation by implementation of Industry 4.0.

Since factories comprises many different departments and countless business processes, like storage, transportation, and maintenance, it is apparent that an instant introduction of smart manufacturing is absurd. To push towards smooth adoption of Industry 4.0, it must be identified what processes are sub-optimal and ready for improvement. Experience in numerous complex factories demonstrated that raw material supply and planning is generally one of the major bottlenecks for fluid run-through in production processes.

1.1.2. Competitive advantage

Previous section already hinted upon the possibilities associated with the Industry 4.0-portfolio. Increasing the efficiency is just one of the many drivers for this innovation. Efficiency is something that can relate to the production time, costs or maybe to the amount of faulty products running out of the factory (Wang *et al.*, 2016a). In the end, efficiency is all about the money, i.e. reducing the costs per produced unit. Being able to produce at lower costs opens multiple business opportunities, ranging from reinvestment, taking higher profit margins or reducing the price per unit to increase the output.

Over the last years profit margins have been diminishing due to the increase of global supply chains and the rise of the cheap Asian production supply (Manavalan and Jayakrishna, 2019). Bal and Erkan (2019) specifically focused on the competitive power of industry 4.0 within the increasing degree of globalisation. Bal and Erkan (2019) describe this competitive power using the model by Porter (Porter, 2008). Porter's Five Forces Model distinguishes between the following five business forces:

1. *Existing competition;*
2. *Potential of new entrants;*
3. *Bargaining power of suppliers;*
4. *Bargaining power of customers;*
5. *Threat of substitutes.*

So for every company the degree of competition can be determined by assessing to what extent items 2 to 5 are present. For example the model demonstrates that companies producing 'simple' and cheap products, like smartphone cases, face a high degree of competition, because of the high risk of substitutes, new entrants, and the bargaining powers of suppliers and customers. Contrary, the production of specialty products, like a recently invented medicine, display a lack of competitiveness.

Within this competitive field, Porter implies three key concepts that enhance the competitive advantage; cost leadership, differentiation and focus (Porter, 2008). In every degree of competition, competitive advantage aids future progress of the company, but is not a mandatory prerequisite. However, it is especially important that companies operating in a highly competitive landscape, should apply at least one of the three key concepts. Fortunately for the manufacturers going through digital transformation, all these three concepts can be found in the Industry 4.0-philosophy:

Cost leadership infers the economies of scale, meaning that a company can produce a high volume of goods that are distributed at a relatively low cost (Bal and Erkan, 2019). As mentioned in the introduction of this chapter, Industry 4.0 is characterized by its ability to significantly improve the efficiency. Consequently, the costs are reduced and/or the productivity increases, both indicating that cost leadership is the foremost trait of the new manufacturing trend.

Differentiation refers to a firm's ability to create a business model that is difficult to replicate (Bal and Erkan, 2019). This includes strategies like aiming for niche markets or simply be evolving the existing product or service and make it better than the product of its competitors. Industry 4.0 covers a wide range of topics, of which smart products is a prominent one. By processing sensors and other smart devices into a product, one could not only generate data for itself, but also use that data to help the customer, therefore adding an extra feature to its product. A good example of this could be found at the HP instant ink product, which is a simple ink cartridge equipped with a small level sensor. As a customer, you simply put the cartridge into your printer and just before the ink is about to run out, you are supplied with a new cartridge to ensure that you will always have a sufficient amount of ink. This is an Industry 4.0-related technology that creates a huge competitive advantage in the realm of differentiation.

The final aspect, **focus** or market segmentation, is a combined efforts of cost leadership and differentiation (Porter, 2008). Every company has some sort of strategy that relates to penetrating a certain market or concentrating on customer groups with specific needs. By focusing on the groups of interest, one is able to outperform competitors who do not adapt their product or services to the specific needs. The former example of the ink cartridge also exemplifies this concept well. Some bigger customers, like printing business, may need many cartridges a week, while home users only need one every month. HP reduced the costs enough that it is able to supply both customer segments on the right time, with the right amount, allowing them to reap the benefits of both markets, rather than have to force a customer to take a minimum amount a week.

Altogether, there is a significant impact to be made on the existing industrial markets. Regardless of the product or service, any company willingly to adapt to the new manufacturing standards is able to make its business more agile, thus obtaining a competitive advantage. Even though the competition might take the same step towards an efficient future, the business opportunities following Industry 4.0 are countless and the competitive advantage awaits those who can utilize the technology the best.

1.2. Problem description

It is quite remarkable that in an era of technological development, increasing opportunities and also the rapid growth of emerging markets (i.e. competition), relatively few companies take the dive into digital transformation. As of 2016, only 16% of the global industry assigned an overall Industry 4.0 strategy (McKinsey Digital, 2016). This rate is utterly alarming, considering that about 100% of the companies will benefit from such strategy. why is this rate so low, and what must change to get more manufacturing businesses into the Industry 4.0-movement?

1.2.1. Practical situation

One of the answers to aforementioned question can be found in the complexity described in subsection 1.1.1 (Lee *et al.*, 2012). Introducing a rather immature technology into a complex environment can cause more harm than it provides opportunities, making the risk not worthwhile. This immaturity evolves mainly from the lack of dedicated information. Many of the Industry 4.0-related technologies are tailored to the context in which the company operates. Consequently, plain businesses can effectively copy these ideas and adapt them effortlessly. Complex businesses, on the other hand, have to reinvent the wheel to even touch upon a few of the opportunities.

As indicated in the introduction of this chapter, a lot of factories become increasingly complex to fulfil the demands of customers. Faster delivery rates, larger product portfolio's and also huge market fluctuations diminished the overall efficiency increase of factories in the past centuries (Wang *et al.*, 2016a). One of the most prominent issues lies within production planning efficiency. Products are the main source of income for the manufacturing business, which makes every percent of production capacity that remains untouched (e.g. due to turn-over time or the lack of raw materials) highly valuable.

As second comes the spatial limitations that factories face. With the increasing demand for tailored products also came the increase in different raw materials and new equipment, all occupying more space than before. In order to keep a healthy balance between products and raw materials, planners have to adjust the numbers constantly depending on the market. The skill to do this sufficiently comes with experience and makes it, therefore, one of the hardest competencies to retain in the company (Kumar *et al.*, 2019; Trstenjak and Cosic, 2017), making this the third challenge.

Finally, the availability of raw materials seems to be a never ending issue. Some materials can be ordered on one day and received on the other, while others require more than 3 months between order and delivery. Add huge market fluctuations, i.e. raw material supply and demand, to the mix and the chaos is complete. Since the data about average delivery times is often fluctuating on many different variables, like market demands, close contact with the supplier is necessary in order to know the actual delivery dates. This personal contact drains a lot of the available time.

In conclusion, the complications coming from raw material supply & planning within complex factories provide a favorable circumstance for Industry 4.0 adoption. However, it is the lack of guidance and mature examples withholding companies from innovating (Oztemel and Gursev, 2020). Besides practical maturity, academic research is one of key drivers for designing the factory of the future.

1.2.2. Academic situation

It is already known that within the Industry 4.0-domain, smart factories will contribute vastly to problems faced in the practical environment, like envisaged in subsection 1.2.1 (Lee *et al.*, 2012; Kumar *et al.*, 2019). The current progress by academic researchers is widespread and covers an immense amount of solutions, usually deeply rooted to the context and origin of a particular problem. This reduces applicability to other cases, because generalization is often left open for future research.

The other specific research approach established, is one that focuses on capturing the concept Industry 4.0. Several articles mention all the building blocks (Mittal *et al.*, 2019), research pillars (Osterrieder *et al.*, 2019) or enabling technologies (Tjahjono *et al.*, 2017) that have been proposed by the academic audience so far. Others try to define which processes need to be touched upon, before full implementation can take place. Altogether, the academic world tries to structure the large amount of information by providing an comprehensive analysis.

However, despite the efforts to create a clear overview of possibilities together with the many specific case studies, a consistent overview of how to implement Industry 4.0 still remains untouched. The bridge, required for practical implementation with the use of academic research, is yet bodiless. The need for an implementation plan, that incorporates practical features and available research on Industry 4.0-technologies, is still awaiting its introduction, even though its urgency is high in this competitive capitalistic world (Yang *et al.*, 2019).

Especially the cooperation between the practical situation; knowing the context and the corresponding interdependencies, together with the academic progress; knowing the newest inventions and understanding the underlying context of organisations, should make the development of a workable Industry 4.0-philosophy much more convenient. However, such connection has only be made to fit the needs of particular businesses. A generic model is yet to be made.

1.3. Research objectives

This research will focus on the currently existing, identified gap between academic research and the manufacturing practice for complex factories; actual implementation. With help of an outline, specified by research questions (Table 1.1), an implementation plan is developed. This implementation framework should be fed with company-specific information, process this data by well-defined questions and finally produce an Industry 4.0-architecture that fits to the company-defined input and aids the treatment of Supply & Planning challenges in complex factories. Although the goal of this thesis is clear, a main research question is settled to provide a straightforward outline for the research. The main research question is as follows: ”How can industry 4.0 be implemented into supply and planning departments of complex manufacturing companies using an implementation framework?”

In order to address this question, we need to subdivide it into more sizeable bits, using sub-questions. The first sub-question raised should provide the mold and boundaries of the framework, in which the implementation plan will be developed. The first sub-question is as follows: “What steps exist in an implementation process and framework?”, and aims particularly to find the right framework that supports an implementation model. This framework provides the overlay in which separate implementation stages are defined.

A second sub-question is raised to address the input parameters and necessary information for the decision process throughout the processing stage. By answering ”How are the key characteristics of a supply & planning environment that are required to construct an Industry 4.0-architecture found?”, one should be able to define what important aspects can alter the effectiveness of the implementation plan. With this information, a starting point (e.g. key parameters) is defined that allows discrimination between different options throughout the decision process. With other words, it is important for the user of the implementation framework to know how his/her raw material purchase and production planning department operates, because when choosing for a particular option during the decision process, the way of operations of that particular company can be harmed. For that reason, it must be carefully examined what the company specific parameters are.

The third sub-question focuses on the current stage of research within the academic domain. Many different technologies have been developed and applied to very specific situations. This sub-question targets all these technologies by answering: ”What are the available Industry 4.0 technologies that aid supply & planning processes?”. The answer should fit precisely into the mold created with the first sub-question. The characteristics should hint upon the previous question and indicate whether a technology, or option, harms or improves the raw material supply & planning tasks.

A final sub-question covers the managerial aspect of implementation. It is of upmost importance to ensure a sustainable and enduring architecture that establishes continuous effectiveness and increasing efficiencies. This topic is captured by applying a ’check’-stage during the design science; ”What must be incorporated to develop a sustaining process that fits into the company’s culture?”.

	Research Question
Main	How can industry 4.0 be implemented into supply and planning departments of complex manufacturing companies using an implementation framework?
Sub.1	What steps exist in an implementation process and framework?
Sub.2	How are the key characteristics of a supply & planning environment that are required to construct an Industry 4.0-architecture found?
Sub.3	What are the available Industry 4.0 technologies that aid supply & planning departments?
Sub.4	What must be incorporated to develop a sustaining process that fits into the company's culture?

Table 1.1: Overview of the research (sub)-questions.

Current Industry 4.0-adoption, as conceptualized in subsection 1.1.1, still hampers because of the lack of implementation knowledge. The main research question of this study addresses this problem and has as goal to construct a full implementation framework. That makes the main research question ambiguous, both a question that is slowly answered throughout the research and a research objective that evolved after answering; a designed implementation model specifically tailored to supply & planning management in complex factories. This implementation model should help companies to consider what technologies to implement (and how) for creating an efficient (automated) production planning process as the basis for a shift towards Industry 4.0. Thereby also aiding further adoption of Industry 4.0 into the manufacturing industry.

The main justification of involving a practical mindset into this academic report, is the predicament of novel developed technologies without actual applicability within the industry yet. On the other hand, some practitioners integrate smart applications while not employing its full capabilities. In both cases there is a uncovered space, which will be both addressed in the implementation model of this thesis.

1.3.1. Practical goals

Multiple reasons for the absence of adoption of Industry 4.0 were already mentioned in previous sections. One of the major concerns is the lack of guidance and necessary talent (McKinsey Digital, 2016). The goal of this research is to find the existing gaps between the existing practices of the manufacturing industry and the readily available information in academic literature. By doing so, a multi-perspective approach (i.e. practice and theory) is done and converted into one model that can be used by manufacturing companies to improve their current operations.

To dilute the content to a more manageable size within the time restrictions of this thesis, the main focus is that of raw material supply & planning operations within a manufacturing environment. Within complex factories it is known these supply & planning processes are difficult to improve and are often the pain point in fluent operations (Manavalan and Jayakrishna, 2019). Targeting this business area with the implementation model serves the foremost issue straight away and will simultaneously develop in-house competences to further unfurl the industry 4.0-related opportunities in other business processes.

By only providing an overview using the implementation model, tailoring efforts are enhanced significantly. Providing multiple options at each implementation stage enables the practitioner to apply the most efficient technology/methodology for his/her case. Subsequently, the applicability of the model evolves to become more effective, which on its turn reduces the risk associated with digital transformation, thus removing one of the adoption barriers (Nilsen, 2015). Furthermore, this allows the same model to be applicable at any degree of digital sophistication (e.g. no Industry 4.0 at all or fully integrated Industry 4.0), implying that it could be used over and over again just to further enhance the existing degree of digital transformation.

Over the course of the implementation of several digital solutions, a company becomes aware of the opportunities and starts to reap the benefits when doing so. This fragmented learning curve is a valuable asset and is therefore incorporated into the implementation model. At first, a mere guidance should help to set directions and pinpoint the low hanging fruits. With every incremental stage, operations become more efficient and the required technologies get more sophisticated. In doing this, the practical mindset is key, as it imposes simple solutions to difficult problems and not the other way around. McKinsey Digital (2016) mentions after all: *"Don't be afraid of 'workarounds' today, but start laying the IT foundations for a more robust solution tomorrow"*. With every step taken towards an autonomous Industry 4.0-inspired smart factory, a new business opportunity is introduced.

Besides these model-related goals, there is a surplus of digital transformation-related goals. By aiding the existing adoption rate through incentivizing easier and quicker implementation, a significant part of the transformation-related goals are attained as well. Outcomes from full adoption of the smart manufacturing principles along the wide range of the manufacturing supply chain vary from lowering costs up to providing cheaper sensing solutions in the future (SMLC, 2011). The Smart Manufacturing Leadership Coalition identified 6 overarching goals as a result of smart manufacturing:

1. Technology Innovation and Economic Health;
2. Agility;
3. Resource efficiency;
4. Safety and Confidence;
5. Maximizing talent and skills of the *Next Generation Workforce*;
6. Sustainability.

Altogether, the practical goal of this research is ambiguous, as in aiding practitioners to overcome existing adoption barriers while contributing to the bigger picture illustrated by SMLC (2011). In the era of intense global competition, exponential growth in information technology, and increasing business performance, this implementation model awaits a welcome introduction.

1.3.2. Scientific relevance

Osterrieder *et al.* (2019) was one of the many researchers that focused on structuring the existing literature into sizeable sub-divisions in order to streamline the excess of information about industry 4.0. In doing so, Osterrieder defines the key constructs of the ongoing innovation based on the widespread terminology. This paper alone, already illustrates the existing difficulties with which the scientific world has to deal. After identifying 8 'research pillars' by examining over 100 articles, they conclude their story with the claim that their study provide a solid basis for further development. Thereby presenting a long awaited literature clarification model.

However, another paper by Mittal *et al.* (2019), shows the imbalance in the academic world of Industry 4.0 by introducing 17 different building blocks compared to that of Osterrieder *et al.* (2019). The urge for these descriptive models becomes higher as the amount of published articles scale logarithmic and consensus on terminology is abandoned. Simultaneously, newer innovations find its way into the incomprehensible concept 'Industry 4.0', deteriorate the fuzzy perception even further.

This thesis does not focus on clarifying the terminology nor arranging them into a structured model. However, by assessment of the many different articles, insights into the core concepts of Industry 4.0 are gained. As a result, concepts can be derived and aligned with a proper practical example that allows further clarification like that of Osterrieder *et al.* (2019) and Mittal *et al.* (2019), for one to comprehend the underlying principles of Industry 4.0. Therefore providing a basis on which future research can close the gap between academic and practical relevance.

Moreover, this thesis contributes from an academic perspective to the field of digital transformation by providing insights on practitioner's perceptions and traditions. Researchers on the topic of Industry 4.0 can add this valuable information to their research to better understand the core needs of successful implementation. Information from the industry is seemingly vital to develop more relevant and useful technologies, as is shown in the past few years.

A final attribute of the scientific relevance of this thesis is prescribed to the relatively wide range of applications that will be touched upon. The majority of present literature is solely describing the employment of a particular technology, after which this is tested and analyzed. Research studies like these offer valuable information within a particular context and are obviously incredibly limited in terms of generalization. With the model, presented in this thesis, the description of these technologies is combined to make it both simpler to comprehend and more applicable.

1.4. Research methodology

Just combining knowledge from practitioners and scientific literature into one large chapter is not sufficient to be considered a model. Design science is the art of development of a model by going over a multitude of steps that are required to sophisticate the model, thus increasing it relevance. Appendix A Design science describes the establishment of a basic design science model, which postulates the outlines of the thesis research. The Design Science shall at minimum include three elements: *"conceptual principles to define what is meant by design science research, practice rules, and a process for carrying out and presenting research"* (Peffers *et al.*, 2008).

Design Science research in this thesis is described as the development of a model, based on practical and scientific information/experience. The model itself shall be dedicated to practitioners of the manufacturing industry, who are assigned with the difficult job of digital transformation. The model should provide, and is not limited to, models, methods and constructs devoted to technical or social advancements, solving the existing business problem of companies that find it difficult to effectively implement Industry 4.0-related technologies. It's *"utility, quality and efficacy"* (Peffers *et al.*, 2008) shall be rigorously evaluated.

The research outline of this thesis will follow the Design Science Research Methodology (DSRM) approach as depicted in Appendix A Design science. This design science model enables full coverage of all important aspects required during this thesis and follow the three key elements of design science portrayed by Peffers *et al.* (2008). Since the model is rather rudimentary, a slight adjustment to fit this research' goals helps to delineate the separate topics to cover. A visualized, adopted, version can be found in Figure 1.1.

Problem identification and motivation is covered in chapter 1, the introduction. Prior to the thesis project, a research study was conducted to explore the current status of Industry 4.0 and smart manufacturing in the literature. This information led to the identification of the existing gap, namely the lack of actual implementation within the industry and the significant irrelevance of scientific research. Subsequently, a new research topic was born, resulting in this thesis project. Multiple data sources, e.g. Scopus, Google Scholar, were addressed to align personal experience with existing data. Altogether, this information justifies the value of a solution, thus defines a clear problem and motivates the need for such a model.

The second stage of this research focuses on the objectives of a solution, including the evaluation what is possible and feasible. At first, it is essential to define the overlay of such implementation model. The goal of Design Science is to create an artefact that includes all vital stages for which it is made. Consequently, the first thing to consider is what steps are required to successfully implement smart principles into a raw material supply & planning environment. This is discovered by performing interviews on Industry 4.0-practitioners and doing a literature review to finally answer the first sub-question: "What steps exist in an implementation process and framework?". In second comes the need for examination of a typical supply & planning environment to effectively dedicate the model towards a generic applicability. The corresponding sub-question: "How are the key characteristics of a supply & planning environment that are required to construct an Industry 4.0-architecture found?" should hint upon the boundaries of the supply & planning environment. Thirdly, one must collect the resources required for the knowledge about the current situation. An important part of the objectives will be the literature study. Investigation must indicate what technologies are available within the Industry 4.0-domain. This will hint upon the possible improvements that can be made, either quantitatively or qualitatively. Next to the previous mentioned sub-question, this part of the research also addresses the

Process step	Problem identification	Objective definition	Design & Development	Demonstration	Evaluation	Communication
Research question	*Research relevance*	*Sub-question 1, 2 & 3*	*Main question*	*Application*	*Sub-question 4*	*Main question*
Data:	- Literature & individual experience	- Literature & individual experience	- Generic	- Generic	- Individual experience	- Full study
Source:	- Literature analysis & general observation	- Literature analysis & interviews	- Previous process step	- Case-study by modelling	- Interview	- Multiple
Type:	- Articles & notes	- Articles & tacit knowledge	- Articles & notes & tacit knowledge	- Codified data	- Experience	- Multi-method
Focus:	- Thesis kick-off	- Research goals	- Design of framework	- Applying framework	- Usability	- Iterate to final design

Figure 1.1: Process projection for thesis report.

third sub-question: ”What are the available Industry 4.0 supply and planning technologies and what are their characteristics?”.

A third stage comprises the design and development and will conclude the previous two stages into practice. Through this phase the implementation model will evolve. The focal point of designing the artefact is determining its desired functionality and its architecture. Using the implementation stages identified in previous chapter already provides a basis in which multiple constructs, models and methods are developed. Moreover, the data obtained via interviews and the literature study are casted into the defined mold. To attain rigor and efficacy, attention is paid to the examined case studies, in order to align the existing research with the established outcomes to avoid known pitfalls from infiltrating the implementation model.

Shortly after creating the model, it must be demonstrated how the model works and performs. A case study, executed at a complex (agriculture) fertilizer factory, allows full testing of the framework by following the implementation procedure. Because the required resources for actual implementation are not in place, an artificial approach is taken. The implementation model consists mostly of analysis and planning stages, which do not require actual implementation. However, the stages that do, are demonstrated by explaining the procedure and assessing the possible outcomes, based on the examples (i.e. case studies) at hand.

A next stage, evaluation, focuses on analysing the results obtained during the demonstration phase. With this analysis, iteration on the model can be performed, i.e. optimizing the malfunctioning steps. Moreover, this step enables the answer to the final sub-question: ”how to develop a sustaining process that fits into the company’s culture?”. This part is already addressed during the literature review, but is further specified when applying the case study, because it allows to pinpoint what issues could evolve by implementation.

The final stage, communication, combines every part covered during the research. The iterated model itself, including its abilities is showcased in the final part of the study. The utility, novelty and the rigor of its design are exhibited in the communication phase, to instruct the effectiveness and usefulness to researchers and practitioners of the manufacturing industry. Furthermore, the shortcomings and recommendations for future research are provided in order to further develop the model and adapt it to separate environments.

1.5. Report structure

The report is structured similar to the DSRM process by Peffers *et al.* (2008). Chapter 1 concludes the problem identification stage and served as introduction to the thesis research. In chapter 2 we provide a literature study that follows the details devoted to the objective definition stage by the DSRM model. Simultaneously, sub-questions 1 to 3 are answered as they are required for design & development stage. Chapter 2 also describes the methodology and results of the interviews that were used for the construction of the practical background. The interviews and literature combined form the basis for the framework design which evolves in Chapter 3. Concluding the design, a case study is executed at an agriculture fertilizer manufacturer which is perfectly suited to the constraints given in this chapter (i.e. complex supply & planning). Chapter 4 will elaborate upon the demonstration and evaluation by performing the case study, and thus testing the model. To conclude the main concepts of this thesis, chapter 5 offers the limitations and reliability regarding this research project. A final chapter, chapter 6, is dedicated to conclusions, reflection, and recommendations in which the model’s outcome is contemplated and concluded.

2
Literature review and background

In the objective definition phase, the literature review is considered to be essential for further development. Literature studies help researchers to find present progress on a particular set of topics throughout the scientific domain. Especially for a topic comprising Industry 4.0, collecting information is a tedious job because of the large amount of interchangeable and fuzzy terms. Moreover, the broad concept of Industry 4.0 involves many different streams, such as technology introduction, literature structuring, and identification of its potential (i.e. people, planet, profit). Finding useful and applicable work in this large pile of interrelated topics is difficult and requires a delicate research approach.

Two different selection approaches are used to acquire tenacity and efficacy in the article selection process. First of all, a large information collection strategy is applied, which will grasp the broad sense of the current research status, as well as introduce me to the topics at stake. This broad searching strategy was employed during the research study before the thesis even started, however, is of upmost importance to understand how articles were read and selected. The first conducted literature study is further explained and described in Appendix B Literature study.

The second approach is dedicated to more specific cases to elaborate on the topics covered in the session of Appendix B Literature study. Retrieval of a wide range of subjects is required to develop the understandings on the go. Literature about statistics, design science, framework development, Key Performance Indicators (KPI) selection, and quality improvements are collected whenever found necessary as the need for it arises. More specific cases, derived from the initial literature study, include the search for case studies, research on procurement and warehousing, and Industry 4.0-related challenges. All this literature is found on the spot and include similar terminology as described in Appendix B Literature study, however, is also reinforced with the aforementioned needs.

Equipped with the diverse selection of information, the literature study is conducted. The aim of the literature study is to create a better understanding of the raw material supply & planning within the context of the factory of the future. Simultaneously, research questions are addressed within this context by forming an appropriate answer based on the provided literature. Finally the chapter is concluded with a GAP analysis that briefly elaborates upon the indicated gap of section 1.2.

2.1. Supply chain & operations

Raw material supply & planning as introduced in chapter 1 is one company's efforts to participate as a small node in wider web of complex interconnected companies, called the supply chain. To understand a company's contribution to this sophisticated network of flows (i.e. cash, materials and information), we must exemplify the bigger picture (Pundoor and Herrmann, 2006). Moreover, the basis for successful participation in this gigantic system is one's capability to efficiently plan the operations, making supply & planning a good indicator for performance.

A supply chain consists of many different processes and flows that are continuously shifting speed and size. Therefore, careful examination of such complex network becomes hard and is difficult to comprehend. Pundoor and Herrmann (2006) put a good effort into describing the supply chain with a minimalist and straightforward approach by dividing three flows to consider: material, information, and cash. These three flows of resources are collectively exchanged between a network of suppliers, manufacturers, distributors and retailers (shown in Figure 2.1) that have the combined goal of turning raw materials in products for customers. The distinction between these three flows is the value-adding nature; materials become more valuable for the customer who is going to use it, making it flow downstream. Information flow, on the other hand, contains all the information that is needed throughout the creation of a product, including fulfilment data. Finally, the cash flow, moves upstream, making the customer pay for its gained value when buying the product.

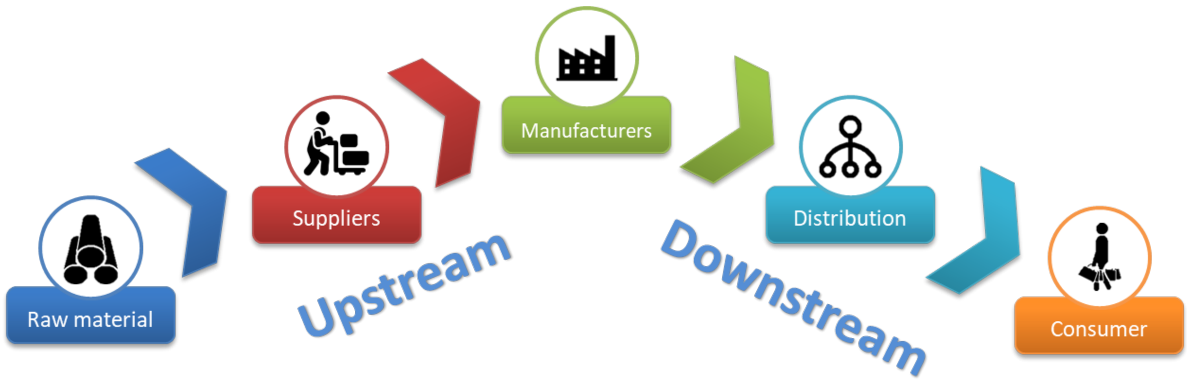

Figure 2.1: The key supply chain nodes visualized.

Every supply chain involve many stakeholders who are all adding their bit of value to a product. Although the way of adding value to the product differs; e.g. transport, merging products, or mining raw materials, the nature of operating these stakeholders is essentially the same (Pundoor and Herrmann, 2006). By means of simulation, (Jain *et al.*, 2001) modelled a high-level supply chain by including forecasting, procurement, fulfilment and replenishment. In doing so, they identified four characteristics that apply to each stakeholder within the supply chain process. Moreover, describing the effects of one company onto another with high detail.

The focus of this literature review is the domain of supply chain together with that of smart factories. In order to generate a smart supply chain, one should adhere to the three integration levels of Wang *et al.* (2016a), Tjahjono *et al.* (2017) and Saucedo-Martínez *et al.* (2018), visualized in Figure 2.2. The first integration level covers horizontal integration, meaning that different corporations are connected to each other for fast product flows through the supply chain. The second level covers vertical integration, meaning a full smart factory. Finally, the end-to-end digital integration of engineering across the value chain. Difficulties that these integration levels should overcome are global competitiveness, lack of adaptability and "go to market time" (Manavalan and Jayakrishna, 2019).

Supply Chain Management (SCM) covers a wide range of different business processes, namely every step within a product life cycle, derived from the four main tasks (i.e. forecasting, procurement, fulfilment and replenishment) (Jain *et al.*, 2001). The stochastic nature of SCM becomes more apparent when reading the work of Manavalan and Jayakrishna (2019), who identified what perspectives of the word 'supply chain management' were used in the literature. Definitions ranging from *"Organizational behavior perspective"* to *"Optimization of value chain perspective"* all fall under the broad concept of supply chain management, but define a different scope. In order to further delineate the topic of this study we introduce the *"planning perspective"*, which aligns a stakeholder's approach of participating in the total Supply Chain. Therefore, specifying the role of this research into a wider network of interdependences.

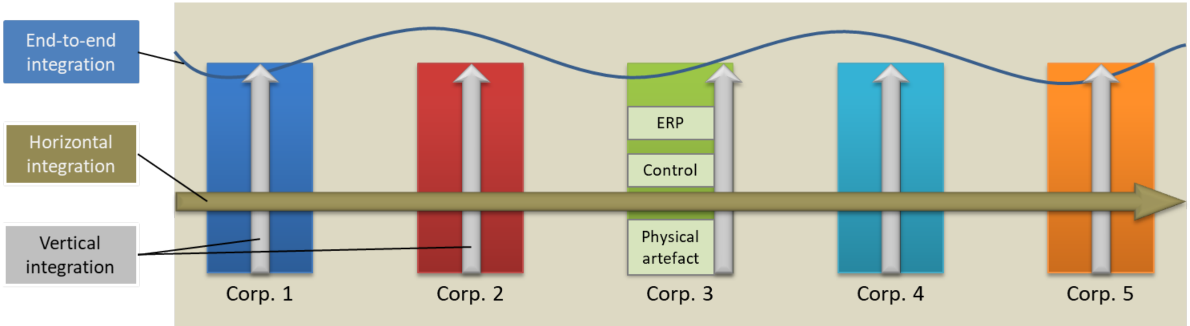

Figure 2.2: The integration levels, adapted from Chaopaisarn and Woschank (2019). ERP is the abbreviation for Enterprise Resource Planning, a commonly used planning tool in large corporations.

The advancements of the supply & planning in smart factories can be enormous. Nowadays, planners have the daily task to plan the production process according to daily incoming manufacturing orders, availability of raw materials, and availability of equipment and personnel. All these decisions can be made quickly and in an efficient manner by applying smart algorithms when the data is available. Useful planning software and tools are slowly finding their way into the market. However, increasing resistance of older, non-technology-educated personnel and the lack of experience with big amounts of data, become a burden for further development (Kumar *et al.*, 2019; Trstenjak and Cosic, 2017). Hence the need for an integrated autonomous system that connects supply chains on an end-to-end basis.

2.1.1. Supply & planning

Operations in complex factories involve a multitude of tasks that have high momentum and require careful alignment to avoid unnecessary inefficiencies. Separate departments work in close collaboration to fulfil the demands of the organization; production and sales. Especially in light of the large amount of supply chains at hand, the operations of one particular factory within this supply chain can have a huge impact on society. Even stagnation at just one of the operation tasks, e.g. planning, can snowball into the downstream chain with significant market effects.

To define this small, yet important, piece within the total supply chain, an operations process flow for factories is designed. Figure 2.3 illustrates the six basic business processes performed at complex factories. Note however, that these processes are not put into order. Every company within a particular supply chain has its own unique specified version of this business process, but the overlay depicted in Figure 2.3 describes the general business for complex factories. The contents of each stage are further described below the picture.

Figure 2.3: Operations process for complex factories, including common restrictions related to the process step.

For most factories, a **forecasting** stage is required to start to purchase raw materials with long lead times, but also to plan ahead depending on the intensity of seasonal fluctuations, e.g. preventive maintenance. Multiple formats of manufacturing supply are commonly used; Make-to-Order (MTO), Make-to-Stock (MTS), Assembly-to-Order (ATO), and Engineering-to-Order (ETO) are just a few of the available manufacturing systems (He *et al.*, 2014). These different ways of manufacturing allow companies to supply their customers in a flexible manner, but often at the cost of efficiency.

In the next step, sales occurs and **production orders** are placed. Regardless of the forecasting method, orders can come at any time and will depend on the manufacturing system in play. If the order contains the request for a customized item, the likelihood for it becoming a Make-to-order product is high. As a result, the product is still to be made and must fit into the production planning. In contrast, if the order requires a commonly sold product, it might be in stock and the consecutive steps (i.e. planning, purchase, production, etc.) are less likely to be affected (Kumar *et al.*, 2019).

According to these orders, and in compliance with the forecasting, a **production planning** is established. This production planning combines former information and also determines what is possible and what not (i.e. based on available resources and capacity). Adherent to the manufacturing systems, MTO and MTS products are scheduled into a pre-determined time period. Some plannings are dedicated to just one week, while others cover a whole month of production orders. Consequently, the orders can be placed up to a particular time to avoid regular alterations in the planning.

Raw materials are **purchased**; according to the forecasting for long lead time materials, and according to the actual planning for short lead time products. A huge part contributing to the raw material purchase is the process called procurement. To keep a strategic advantage, like the one described in subsection 1.1.2 by Porters' Five Forces model, a company can determine its suppliers' bargaining power by applying tactical procurement. Tactical procurement involve the sourcing of different vendors, as well as setting the terms for the different agreements. In practice this means that manufacturers buy the same resource from various suppliers to maintain a competitive price and avoid monopolies. Consequently, raw material purchasing is no longer a straightforward job of just buying the required materials, but must also to adhere to the constraints (i.e. agreements) from the different supplier parties.

Storage of raw materials is a continuous process that evolves along the chain. During the forecasting stage, a purchaser is already checking what the future stocks will be, depending on the forecasted demand. Simultaneously, the production planner is assessing the incoming materials as well as the existing stocks to tighten the warehouse stocks while ensuring that enough materials are available when necessary. Altogether the warehouse process is a result of other processes and has to work within these constraints. However, the warehouse process is one of significant impact, as a slight delay in internal warehousing can stagnate the production or transportation significantly Reaidy *et al.* (2015).

The one to last stage, in which the actual business value is established, comprises of **production/ manufacturing**. Production is the sole action of taking the raw materials, convert them into a product according to the production planning and then put them into storage for transportation. In current practices, the production process receives the most attention as managers see them often as the only value-adding stage of the operations process (Rosin *et al.*, 2020). This view caused that many companies addressed the inconvenience of their manufacturing systems by adding newer and better equipment and technologies. As a result, most of the factories are running close to their highest output and become more dependent on external effects. Consequently, the manufacturing process gets limited in its output due to externalities, but is not able to coope with the changing demand, thereby making the managers' view a self-fulfilling prophecy in which the manufacturing process is limiting the others.

In line with the illustrated process of Figure 2.3 the produced goods are **stored** directly after production before they are transported to the customers. This second storage process differs from the first in the sense that its inflow is continuous and its outflow is transport-based, which is the opposite for raw materials. Therefore stagnation in transportation or producing MTS products only will result in an overflow of material coming into the warehouses. This is unfavorable as warehouses provide only limited storage capacity.

Industry 4.0-technologies are primarily focused on improving just one of the depicted business processes rather than addressing the system as a whole. Some of the proposed Industry 4.0 technologies can have a tremendous impact on the challenges that arise with the growing demand for flexibility within the different departments. S&P is part of the supply chain management (SCM), which has already been investigated by various researchers, like Manavalan and Jayakrishna (2019); Chaopaisarn and Woschank (2019); Do Chung *et al.* (2018). Therefore joining the best of both worlds, by connecting the smart supply chain methodology with the opportunities in the complex factory operations process.

2.1.2. Improvements

Although the solutions and opportunities using Industry 4.0-related technologies into the raw material supply & planning environment are promising, alternative ways of improving operations are plentiful as well. Two well-known and widely applied methodologies for improving manufacturing operations are lean and agile manufacturing (Soltan and Mostafa, 2015). Both concepts have shown their efficacy in different corporations all over the world. By means of a systematic approach, many companies benefit through assessing the existing performance by creating a structural overview. Consequently, a significant part of the industry already adheres to the techniques employed in both agile and lean methodologies. Subsequently, the need for alternative technologies seems less attractive, because of the significant investments already made for agile and lean, and the perceived similarities (i.e. improving efficiency).

Although the two terms often come hand in hand, Agile and Lean indicate completely different approaches to process improvement. Lean is the process of developing a value stream, which can be similar to the supply chain stream described in the introduction of this chapter, in which all waste is eliminated (Soltan and Mostafa, 2015). Waste is perceived in the broadest sense, e.g. time, money, and materials. Agile, on the other hand, is dedicated to using knowledge and virtual assets in a smart way to exploit profitable opportunities. Both ways of perceiving the four supply chain processes; forecasting, procurement, fulfilment, and replenishment, can offer different insights and thus different solutions (Jain *et al.*, 2001).

In the lean philosophy, a company uses concept, quality, and lead time as market qualifiers, which on their turn enable cost reduction. A variety of practices are available to achieve cost reduction through conceptualization of waste barriers inside the business process, including Just-in-Time (JIT), Kaizen, Total Quality Management (TQM), and equipment management. All these methods target a particular piece within the supply chain and allows one to find a typical waste source, after which this waste can be eliminated. The types of waste, specified for lean are (Soltan and Mostafa, 2015):

1. *Overproduction;*
2. *Defects;*
3. *Unnecessary inventory;*
4. *Inappropriate processing;*
5. *Excessive transportation;*
6. *Waiting;*
7. *Unnecessary motion;*
8. *Underutilization of employees.*

The list clearly shows that waste can also be found in rather non-clear-cut stages. For instance, having an unnecessary inventory clearly follows the 'waste'-philosophy from the word 'unnecessary'. However, many companies were unaware of the far-reaching costs associated to 'unnecessary' stocks. As a result, stocks were never perceived as being 'unnecessary', but rather as a safe buffers. Since the introduction of lean in 1991, a lot of corporations altered their inventory strategy to avoid 'unnecessary' costs, and with success!

Agile working is the execution of improvement studies focused on making short and cyclic processes. Other than the focus on production processes of Lean, Agile targets the existing business processes and tries to embrace these into a dense version of it. Although Lean and Agile are considered to be separate methodologies, their practices often show a lot of similarities. JIT, TQM and decision support systems are just a few of the interchangeably used methods (Soltan and Mostafa, 2015). As a result, applying the Agile-philosophy on a company structure proceeds to eliminate unnecessary tasks, thus reducing its waste. Multiple spin-offs of this methodology emerged over time, of which Scrum is the most well-known, but also Kanban and DSDM are increasingly applied to the manufacturing industry (Soltan and Mostafa, 2015).

Even a combination of the two strategies, called leagility, is a useful developed philosophy (Soltan and Mostafa, 2015). Despite the methodologies providing a solid structure for development, the execution still relies on own interpretation and application. Moreover, there are known cases where applying the methodologies in a 'wrong' manner caused even more harm to the organization. With this in mind and including the growing knowledge about effective improvements, we must define a clear-cut strategy for the digital transformation that utilizes the already existing knowledge.

2.1.3. Critical parameters

Especially when exercising improvement studies, and knowing its possible harm, attention must be paid to the key enablers of the business' process. In subsection 2.1.1 the essence of the raw material supply & planning process was illustrated. Within a large complex network of interconnected companies, this planning process is a key driver for organizational success as well as the main link between internal operations and the surrounding supply chain. Therefore, a considerable number of companies addressed their supply chain and planning performance over the last decades. Applying various tools, including Lean, Six Sigma and Agile derivatives, organizations have tried to improve their current operations and established a competitive advantage in a prominent manner (Rosin *et al.*, 2020).

Now the Industry 4.0-philosophy becomes eminent together with its perceived utility, we can apply some of the lessons-learned from the decades of leagility implementation. Especially the performance measurements evolved in the leagility-philosophy allow us to find critical parameters for successful and effective implementation. Locating the performance parameters of a good supply chain planning help to address the existing bottlenecks - by means of benchmarking - and also provides a way to measure effectiveness of said implementation.

One of the applied analysis tools, Supply Chain Operations Reference (SCOR) model, is particularly used to map, benchmark, and improve supply chain operations. The wide range of topics covered in Supply Chain Management (SCM), e.g. flows of information, flows of cash, and different nodes in a network, make it a difficult topic to comprehend. A model like SCOR helps to organize the different subjects to cover and offers a systematic way to evaluate the performance. SCOR comprises of three key parts; (I) modeling tool that standardizes business processes as building blocks, (II) a set of Key Performance Indicators (KPI's), and (III) a tool to compare KPI's with other companies (Persson, 2011). Especially these metrics provide organizations a way to handle the situation by understanding its operations, a particular important aspect for digital transformation.

At first, the SCOR model focuses on the existing business processes within a company. This first defining approach is used in a variety of models, but the SCOR model is particularly effective in explaining the critical aspects of business process modelling by defining degrees of focus; i.e. levels. At level 1, process definitions, the five process types, described below, are amplified. In level 2, process type, the model is enriched with enabling processes as well, like maintenance, overhaul and HESQ (Health, Environment, Safety and Quality). Moreover, the five core process types are further delineated by defining sub-categories, like the difference between make-to-stock (MTS), make-to-order (MTO), and engineer-to-order (ETO) products. The execution of each of these products can significantly differ from one another. In the final level (3), process category, the underlying processes of level 2 are described. Sub-processes such as receiving products, authorise payments and scheduling are specified to create a full overview of all business process required in a supply chain participating operations company.

- **Source/Procurement:** *meeting the demand of raw material, components and other services needed in operations;*

- **Make/Manufacturing:** *actually adding value to the raw materials by crafting a new product;*

- **Deliver/Distribute:** *ensure that the created product is delivered to the next node within a supply chain;*
- **Return:** *receiving returned products from customers, due to several reasons, often captured in a complaint commission;*
- **Planning:** *balancing all other processes by adequate planning.*

The aim of the SCOR model differs slightly from the operations process illustrated in Figure 2.3. This difference mainly evolves around the generalizability of the two processes. SCOR is generally applicable, and therefore focuses on the processes that are similar in each every node of the supply chain (Persson, 2011). The operations process, on the other hand, is merely describing the downstream operations at a complex factory. Since the sole purpose of this research is dedicated to complex factories, this alteration where 'return' becomes obsolete, is perceived more accurate than the generalized 'SCOR'.

With these different processes in mind and knowing how to create a full overview of the business processes (i.e. level 1 to 3), we can dive into the next aspect of the SCOR model. Not only can we now put numbers to each process, we can also define the performance of each of the processes . In line with the lean - waste - methodology, processes can be measured in dimensions like time, costs and unnecessary motion. Numbers like these are perfect for obtaining aforementioned performance by calculating so-called Key Performance Indicators (KPI's). For example, one could calculate the amount of raw material consumption, which is a simple number related to the process. Subsequently, you could determine the average amount of that raw material being available inside the company. A simple division of the two numbers returns the average inventory turnover - representing the time you can produce without replenishment.

By calculating multiple KPI's within the 5 different sections (i.e. agility, responsiveness, reliability, cost, and asset management), you create a better understandin of your process. Especially the calculation of these KPI's, related to the supply chain, establish a benchmark for both the comparison between internal operations versus external operations, as well as the performance increase pre- and post-digital transformation. Targeting those KPI's that are currently under-performing helps a manager to make effective and efficient decisions.

The KPI's related to the SCOR model are also called 'metrics' and are divided into the three levels of abstraction as well. At the very top, level 1, only a few metrics are considered to measure the company's performance effectively, as depicted in Table 2.1. However, the underlying levels 2 and 3 provide more than 4000 additional KPI's dedicated to each separate identified process (Gordon, 2011). Finding the right KPI's for a company's structure is based upon the applicable processes. For instance, there is no need for a company to calculate its packaging reuse number when all products are shipped in bulk trucks.

Performance attribute	**Metric**
Reliability	Perfect Order Fulfillment
Responsiveness	Order Fulfillment Cycle Time
Agility	Upside Supply Chain Flexibility Upside Supply Chain Adaptability Downside Supply Chain Adapability Overall Value At Risk
Cost	Total Cost to Serve
Asset Management Efficiency	Cash-to-Cash Cycle Time Return on Supply Chain Fixed Assets Return on Working Capital

Table 2.1: The SCOR level-1 Metrics, by Gordon (2011).

Although SCOR is a useful method to determine a process' critical parameters, it remains limited to supply chain-related processes. Another view on a company's performance is provided by the Balanced Scorecard (BSC) approach (Díaz Curbelo and Marrero Delgado, 2014). The BSC methodology concentrates on collecting and analyzing management systems. These systems were subdivided into four perspectives to measure operational performance; (I) learning & growth, (II) customers, (III) business process, and (IV) financial (Frederico *et al.*, 2020). With help of the different dimensions of operations a company can align its management properly, perform good communication through the different communication channels within the company, and measure performance. The first perspective to be addressed is learning & growth which provides the basis for the other perspectives. In this perspective it is checked how learning & growth are stimulated within the company. The second dimension; customers, aims at the performance of a company's sales, namely customer satisfaction and customer-enhancing initiatives. Thirdly, the business processes is the intertwined terminology that describes all interrelated tasks within a company. These processes allow a company to exist and to provide its service to the market and society. A final dimension is dedicated to financial, which encompasses all former dimensions and is the result of company's performance.

A company can use the four perspectives to categorize different ongoing processes, like financial and strategic results, which fall under (IV) financial, or technologies which clearly constitute (I) Learning & growth. Figure 2.4 clearly shows the interrelationship between the four perspectives that collaboratively align the company's strategy. In each perspective, one focuses on the objectives, measures, targets and initiatives, thus both enhancing the existing effectiveness and measuring its performance. A few approaches for measuring Industry 4.0 for instance can be found in the paper by Frederico *et al.* (2020), who identified multiple supply chain related attributes that can be measured. For the financial perspective they found among other things: shareholder value, level of cost reduction, and profitability. Business processes, on the other hand, had identifiers like response time, level of flexibility and level of waste reduction. One can clearly see the difference compared to the SCOR approach where the numbers are often determined straightforwardly in the form of a KPI. In the BSC approach, the identifiers become more abstract (i.e. level of flexibility) that cannot be measured, but is the result of thorough investigation and an assessors' own perspective.

Altogether, the two ways of measuring a company's performance allow businesses to find existing low hanging fruits, simply by comparing its own performance versus a benchmarked value. Moreover, it shows manufacturing companies what other processes can be improved other than just the manufacturing process, thus broadening the scope and seeing the potential of Industry 4.0-related technologies. A final benefit of the BSC and SCOR models is the employment within the digital transformation, to assess performance of critical parameters pre- and post-implementation, obtaining the digital transformation effectiveness.

2.2. Smart factory

Smart factory is a concept within the Industry 4.0-domain which is often used interchangeably Osterrieder *et al.* (2019). Though the words might infer similar meanings, this report strictly separates the two. Industry 4.0 in the context of this thesis implies the use of novel technologies within the industry in the broadest sense of the word, e.g. supply chain and logistics. Smart factory on the other hand, indicates the integration of 'smart' technologies into a factory for smooth and easy execution of the manufacturing system.

The importance of implementing smart technologies into complex factories was portrayed in section 1.2. With that in mind, we must identify what is included in a smart factory and how should the factory of the future function. Moreover, the connection of one factory to another, including all steps in-between, make this factory participate in a supply chain as a whole. Therefore we further delineate how the smart factory-technologies integrate into the bigger picture by addressing "smart supply chains". The final two subsections of this section cover the existing adoption barriers and the elements to overcome for companies to take the step towards effective manufacturing.

Figure 2.4: Balanced scorecard approach for finding the right indicators in an operations environment to fulfil the company's strategy, adapted from Kaplan and Norton (2001).

2.2.1. Technologies

Technologies and technological innovation play a key role in digital transformation. Without the introduction of novel technologies and their innovative applications, the industry would keep relying on their existing knowledge which is based upon Programmable Logic Controllers (PLC) and a lot of experience from decision-makers (e.g. planners and procurement) (Saucedo-Martínez *et al.*, 2018). This way of operations involve a lot of human communication and include a significant portion of planning to avoid unnecessary waste.

In the new digital era, we are introducing ways to improve the existing processes by adapting technology to the needs of company. Previous efforts like lean, outlined in subsection 2.1.2, already streamlined business processes significantly, but oftentimes by simply restructuring the process without implementing actual technology. Nowadays, the paradigm shifts towards restructuring data rather than business processes (Frederico *et al.*, 2020). Data was already a key driver within multiple disciplines inside a manufacturing organization, but was never identified as such. Information about customers, suppliers or the status of equipment can all be labeled as data and are continuously used during decision-making processes. However, this data is often static and changes only when communicated correctly, e.g. the production capacity of a factory. Since the production capacity changes continuously due to malfunctioning equipment or due to down-time, a production planner is always reliant on the status information provided by the production department.

All sorts of data are required in various stages of the business processes and at various levels in departments of a company. Streamlining these different data flows and letting them work effectively mainly depends on the technologies used. A wide range of data-related technologies have found its way to business in the past few years. Ever since the introduction of Industry 4.0, companies increasingly understood the importance of data and started to reap the benefits of the technologies associated with it. Since data is a holistic concept, we will define the key enablers defined by various researchers (Mittal *et al.*, 2019; Tjahjono *et al.*, 2017; Rosin *et al.*, 2020; Frank *et al.*, 2019; Dalenogare *et al.*, 2018), combined in 13 key technologies shown in Figure 2.5.

Figure 2.5: The 13 overarching technologies enabling digital transformation in Industry 4.0.

Virtual and augmented reality are commonly associated with the consumer markets where subjects like VR gaming have become immensely popular. Within the industry a similar technology is applied where one could dive into a virtual version of a factory and test actions within this virtual environment (Tjahjono *et al.*, 2017). Augmented reality adds a few functions compared to virtual reality. In augmented reality the actual environment is displayed, in which particular objects are modelled. These tools are particularly valuable for training purposes, where new employees can learn real-time by performing 'virtual' actions without harming the real process.

Additive manufacturing evolves from Computer Aided Design (CAD) model or a digital 3D-model construction. 3D-printing, a synonym for additive manufacturing, is the art of solidifying liquid molecules or powder grains into a pre-determined digital shape (Kumar *et al.*, 2019). This is particularly effective for the manufacturing of prosthetics which are tailor-made to the patient. Consequently, in the past few years many businesses emerged upon the 3D-technology because of the high flexibility for custom-made products and the relatively simple technology used.

Miniaturization of electronics is not a technology on its own, but is considerably important in industry 4.0 (Tjahjono *et al.*, 2017). Moore's law is one of the most prominent and well-known explanations of the rapid reduction in size of chips. Due to the increase in number of transistors on circuit chips over time (i.e. Moore's law), the productivity of said transistors become more efficient and also decreasing their size causing the chip's final size to reduce as well. This reduction in size is notably useful to the sensor-techniques employed in the industry, as they are readily integrated into the existing architecture.

Robotics, drones and nano technology follows right after. Innovations like unmanned air vehicles (UAV), sensors and machine learning are effectively improving the production operations (Oztemel and Gursev, 2020). Robotics can be employed with simple sensors, similar to those on a self-driving car. These sensor collect data that help a robot to determine what actions to take. Add a self-learning algorithm, i.e. machine-learning, and the machinery will work without any intervention.

Blockchain is an innovation on its own, which only recently got associated with the smart manufacturing domain (Mittal *et al.*, 2019). For that reason, the applications of blockchain are not clear-cut and its utility is yet to determined. However, the smart contracts principle supported by the blockchain technology enable a large pool of new business opportunities. Smart contracts are the pre-programming of contracts, including its payments, using conditions which must be fulfilled before transaction takes place, e.g. arriving at location B and delivering X tonnes of material. When all data is automatically obtained through sensors, human interaction is no longer necessary as all administrative processes occur through a pre-determined algorithm.

Simulation is already an established brand within the subset of industry 4.0-technologies. However with the emergence of the other technologies, simulation gets a new dimension and utility (Rosin *et al.*, 2020). Simulation based on real-time data help decision-makers with their operational decisions. Analyzing the incoming data and tweaking it to preferred outcomes by simulation are far more accurate than guessing or using limited historic data.

Big Data Analytics is one of the critical aspect in smart manufacturing. Data is collected through several technologies; through others the data is processed, stored and/or forwarded and by the remaining technologies data is used. As can be derived from this explanation, a lot of data is flowing through the interconnected systems, called big data. This large amount of data has to be processed in order to make use of it, which is found in the art of big data analytics (Saucedo-Martínez *et al.*, 2018).

Automatic Identification and Data Capture (AIDC) is the technique of automatically identifying objects, converting it to data, and pushing them directly into a digital environment. Different AIDC methods are present; radio frequency identification device (RFID), bar/QR codes, biometrics (e.g. face recognition), and magnetic stripes Wang *et al.* (2016a). All methods have in common that they measure objects, however, identify based on a different principle, like chips (RFID) or an image (bar/QR codes).

Machine to machine (M2M) communication is the direct communication between devices using wired or wireless networks Oztemel and Gursev (2020). This type of communication is truly important as it provides the basis for data exchange. M2M varies from simplistic forms, where an SMS was send to a GSM when an alarm-system detects a thief, up to advanced methods where a piece of equipment is using the combined data of 20 other devices to predict its future output, like a smart meter in your home.

Cloud technology is at the very center of the data flow. Nowadays, companies do not prefer to adhere to one place only, thus utilizing the full potential of the internet. Through internet connections, data can be stored and retrieved from anywhere around the world. Moreover, outsourcing of data reduces local overhead for the large server systems required to store all that data. Besides the storage capacity of cloud systems, is the capability to install applications on the cloud sources, thereby reducing the demand on local systems.

Cyber security is the immediate response to the increasing use of cloud services (Rosin *et al.*, 2020). Connecting local data to the internet, enables hackers to get access to valuable and confidential information without having to physically enter the production site. Moreover, with the increasing use of robotics, which can be manually operated, the likelihood of dangerous situations due to criminal activities increase significantly. Within the domain of cyber security, countermeasures to this digital infringement are taken.

Business intelligence (BI) is often seen as the overarching employment of digital solutions. By collection of business information and doing data analysis on them, a company can predict future events and anticipate on them. For instance, a company might know that the beer consumption around the Oktoberfest will increase threefold, therefore changing the regular strategy of make-to-order to a make-to-stock to ensure sufficient stocks during this demanding period.

Internet of Things (IoT) is the final technology to be considered. IoT is a true buzzword that encompasses many of the aforementioned technologies. The internet of things is a system of interrelated devices that communicate with each other without human interference Yang *et al.* (2019). This system of devices include sensors, connectivity, and an architecture of interconnected devices. A perfect example of IoT is found in new - technology-intensive - houses which have various devices like lamps, air conditioners, and media devices connected to one smart phone on which the resident can control everything or set it to automatic mode.

In order to implement a smart system using the 13 enabling technologies, it is important to consider what must be taken into account. On a very general level, Yang *et al.* (2019) defined three key backbones that should built towards the 4 layers of the Cyber Physical Systems (CPS) (i.e. smart system) (Chaopaisarn and Woschank, 2019). First of all, data management, i.e. how is all incoming data managed? Secondly, the information processing is addressed, i.e. how is the data, which is required, collected? And finally, the decision-making, i.e. what is decided, depending on which data? Since the three backbones of Yang *et al.* (2019) shows similarities with the 4 layers of Chaopaisarn and Woschank (2019), but without one crucial layer, I will introduce a fourth backbone that needs to be addressed during the implementation. This fourth backbone requires one to think beforehand what data needs to be collected, by addressing the question: "what data is required to make the decisions we want to make?". The 4 CPS-layers and 4 corresponding backbones are summarized in Table 2.2.

Cyber Physical layer	**Data management**	**Aim**
Physical layer	Information process	How is the data, which is required, collected?
Data layer	Data management	How is all incoming data managed?
Cloud & intelligence layer	Decision-making	What is decided, depending on which data?
Control layer	Required data	What data is required for our decisions?

Table 2.2: Connection between Cyber Physical layers and data management processes.

These CPS layers are identical to every Industry 4.0-architecture and help to understand how different technologies collaborate and what each technology contributes to the general architecture (Chaopaisarn and Woschank, 2019). From Table 2.2 it should be apparent that smart systems include solutions and require action at different levels of abstraction. For instance, data must be obtained, thus some sort of physical system must 'sense' what is going on on the factory floor. Something that is being done within the manufacturing for decades using PLC and DCS systems. However, the other 3 layers are already less straightforward due to them being relatively new in the conservative world of manufacturing. Now we know that these layer exist as well, we can dive into the technologies that drive digital transformation and share the Industry 4.0-philosophy.

The very basis of the technologies can be derived from Frank *et al.* (2019) who distinguishes between front-end technologies (i.e. smart supply chain, smart working, smart product and smart manufacturing) and the base/enabling technologies; Internet of Things (IoT), Cloud, Big Data and Analytics. These four broad concepts of technology describe the Industry 4.0-domain in a generic way, leaving out some important aspects. Chen *et al.* (2017) dives deeper into the topic by describing the enabling technologies for each of the CPS-layers, identified in Table 2.2. For each layer, which has a slightly different name, they identified what technologies exist and how these technologies are linked together. Figure 2.6 shows the identified and related technologies for the four CPS-layers.

At the very basis of a Industry 4.0-architecture is the physical layer. In this layer, data is collected and machinery is being operated. Manufacturing systems comprises of a lot of physical assets that perform various tasks simultaneously and collaboratively. This continuous changing state is important information in the overlaying decision-processes like maintenance and production planning. By capturing the state of the equipment, e.g. pressure and frequencies, we can base our decisions on accurate information rather than guessing the state using experience. Data capture is done via sensors specifically designed for that purpose. This means that it must be known beforehand what data needs to be captured, since a pressure sensor cannot measure temperature or vice versa. Typical technologies that are included in the physical resource layer are RFID's, Sensors, PLC's, smart meters and ZigBee routers.

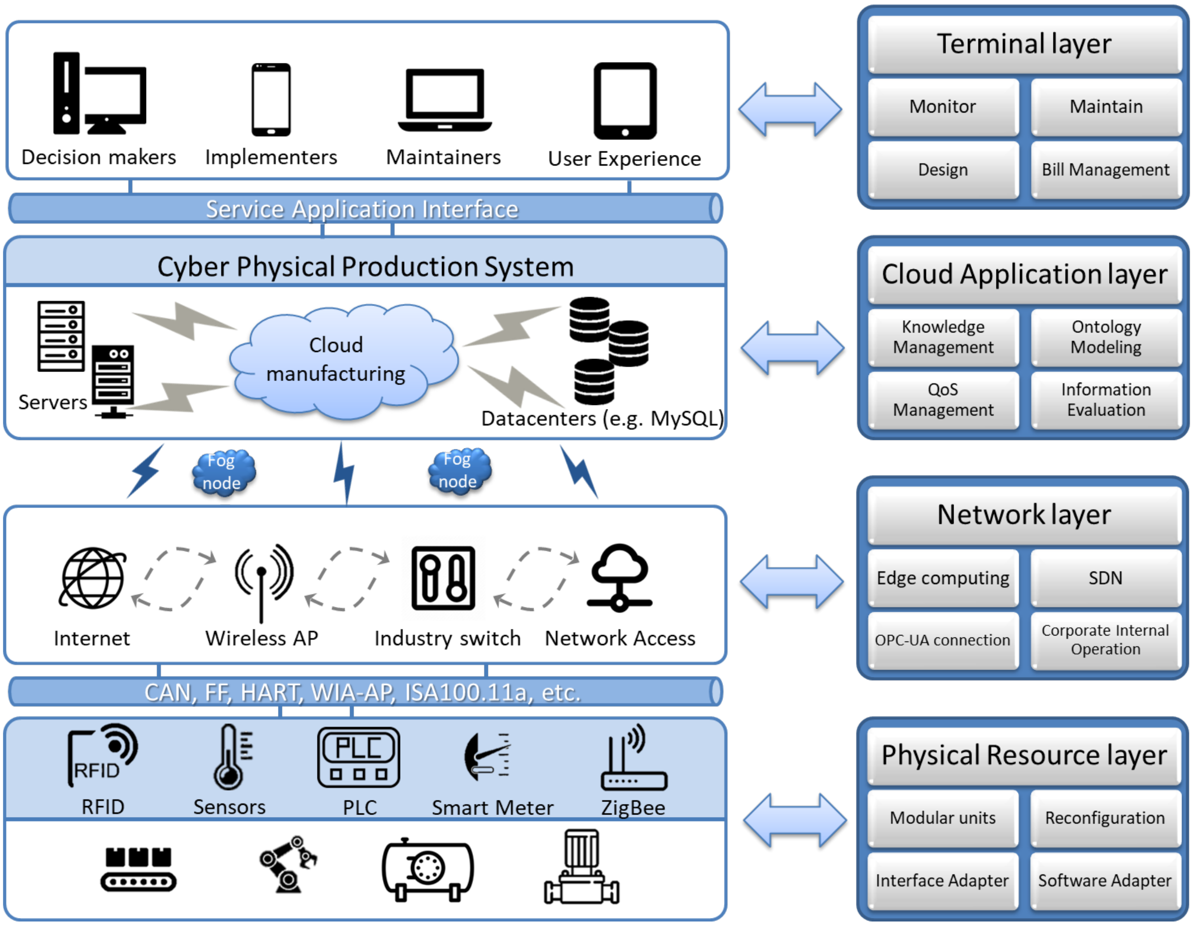

Figure 2.6: The CPS-layers including the corresponding technologies and possible ways of interconnection, adapted from Chen *et al.* (2017).

After the data was collected and combined at a local node (e.g. PLC), the data must be forwarded to a more useful location, like the cloud. This driveway of data is critical, because it can significantly hamper the use and value of data. Similar to a highway; if too many cars join the road, a traffic jam will happen and everyone on said road will reach their destination a bit later. The network layer performs a similar task to the highways and ensures continuous data flow from physical assets to the storage location and vice versa. Because autonomous processes cannot rely on 'experience', they need data to do their decision-making processes. The increase of autonomous processes thus increases the need for data thus requiring larger and efficient 'highways'. Technologies found useful in this domain are in the domain of enternet, wireless AP, industry switch, and access network that rely on the concepts of Edge computing, OPC-UA interconnection, Software defined networks (SDN) and device to device (D2D) communication.

The cloud application layer encompasses the storage section of the data, where data can be stored locally on a server or on a particular database like MySQL or Oracle. Applications, which use the stored data, are also located in this layer. Applications like ERP (Enterprise Resource Planning) and WMS (Warehouse Management Systems) are often deployed in large organizations and aid employees in their decision-making processes.

Finally, the terminal layer incorporates the other three layers as this is the key layer in which decisions are made based upon the bottom layers. Between the terminal and cloud layer lies the service application interface. Nowadays, decision makers can reach their digital information via various tools, e.g. smart phones, tablets, and monitors. However, it is the service application layer that makes the terminal layer useful. Each application has its own user-interface and based upon this interface, a decision-maker decides what subsequent actions must be made, therefore playing a critical role in the process.

Although the lay out showcased in Figure 2.6 can be interpreted similar to existing industrial SCADA (Supervisory Control and Data Acquisition) systems, their differences are significant. Figure 2.7 depicts the difference in a standard automation hierarchy, where consecutive layers of information are involved in the manufacturing process, compared to a CPS-based automation system of intertwined devices, applications, and systems.

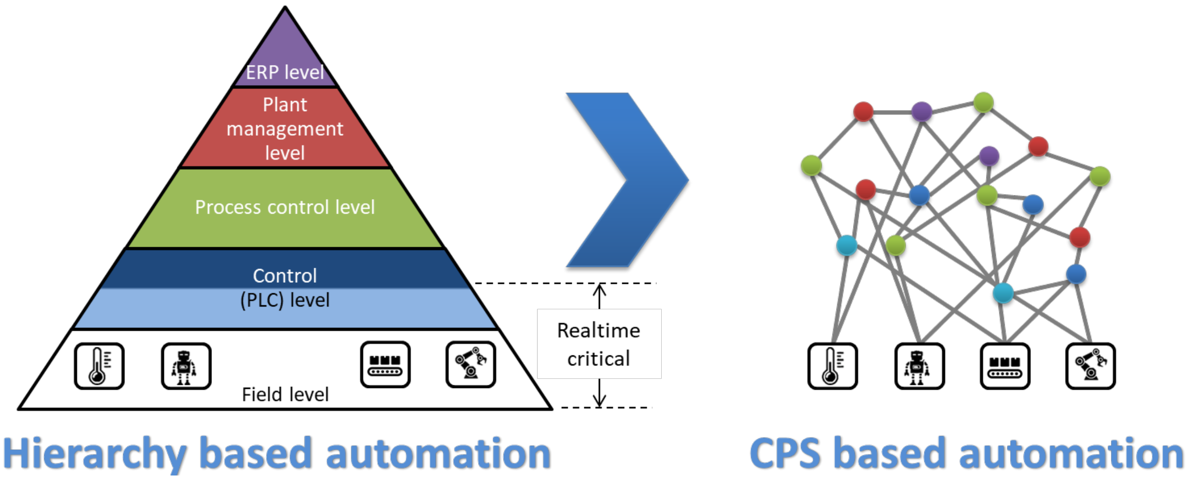

Figure 2.7: The classical automation hierarchy on the left versus the CPS-based interconnected automation as visualized in Industry 4.0, figure adapted from Plattform Industrie 4.0 (2015).

2.2.2. Adoption rate

In subsection 2.1.2 it was argued how companies improve their performance for a few decades now. Consequently, the effectiveness of said methodologies will increase at first because of the learning curve associated with it. However, at some moment in time these techniques become obsolete and their effectiveness diminishes. A complementary philosophy, found in Industry 4.0, will enhance the existing systems and drive new initiatives to improve internal performance. But why is Industry 4.0-implementation still limited as is described in section 1.2, while the concept exists since 2012?

McKinsey Digital (2016) identified multiple barriers at different levels of integration, depicted in Figure 2.8. The top 5 entry barriers; difficulty in coordinating actions, lack of courage, lack of necessary talent, concerns about cybersecurity, and lack of a clear business case are all difficult to overcome, hence the lack of widespread adoption. Especially when looking further into the future, data-related challenges such as ownership, in- and outsourcing, and integration become a burden for fast development.

Not only the 8 challenges depicted by McKinsey Digital (2016) are considered to be the adoption-limiting factors, also the maturity of the different technologies is considered to affect the adoption rate. Although Industry 4.0 presented itself in 2012 and the associated technologies were even known before, a significant portion of the technologies are still in its intermediate stage (Pacchini *et al.*, 2019). For eight of the Industry 4.0-technologies, Pacchini *et al.* (2019) assessed the maturity levels for implementation in manufacturing contexts. This study already left out 5 of the 13 drivers from Figure 2.5 (i.e. simulation, miniaturization of electronics, blockchain, AIDC and Cyber security), likely indicating that these are even more lagging with regards to maturity.

Large corporations are often cumbersome and not able to quickly anticipate on changing markets. Yet they are the ones with the least issues regarding industry 4.0-adoption shown in Figure 2.8, like lack in talent or courage. Smaller businesses on the other hand have relatively low bureaucracy, thus making the adoption of new systems rather straightforward. Nonetheless, these companies do face the lack of talent and courage, making them reluctant of adopting the new systems. Thereby explaining the overall adoption a industry-wide issue.

Among the others, Yang *et al.* (2019) further increases this list of challenges by looking at the technology's end. Latency, bandwidth and interference are affecting the flow and usability of data through the entirety of smart systems. Latency refers to the time interval between actual recording and its response. When employing autonomous systems, one would want at least a similar response time as a human being, but preferably even faster. For example, if the latency for opening a door is 10 hours, no one would ever use that door again. Bandwidth is the width of a particular connection, determining the maximum rate of data that can flow through. The highway example of subsection 2.2.1 is a perfect illustration of bandwidth. Interference is, as the word suggests, the interference of multiple data sources at the receiver side. Data is forwarded by various tools and on the receiving end; a tool must decide which data to use and how to process the data.

So even though the technologies can be beneficial, companies are clearly reluctant to use the technologies due to the associated challenges. The need for new technologies is mandatory due to the aging of the workforce, resulting in a significant experience loss in a few years from now. Add the loss of your competitive advantage to the mix and the risk of holding onto existing practices becomes as high as switching to the newer technologies.

2.2.3. Integration

Due to the increasing importance of industry 4.0-adoption, the integration of it becomes more important as well. Since implementation of Industry 4.0 is considered to be difficult, its employment process should be kept simple and straightforward. Integrating implementation steps into existing methodologies, like Six Sigma, could significantly increase the performance and adoption of the Industry 4.0-technologies.

Dogan and Gürcan (2018) describe this resemblance between Six Sigma and Industry 4.0 by describing both as a 'quality-improvement'. The use of data plays a crucial role in both subjects. Through the collection, analyzation, and utilization of data companies can make faster, more reliable, and satisfying decisions, thereby increasing the quality. Although, the difference is huge (i.e. Six Sigma is an quality improvement method and Industry 4.0 is the art of utilizing novel technologies to manufacture effectively), the goal of both is similar in nature. By providing novel technologies to the solution-portfolio of

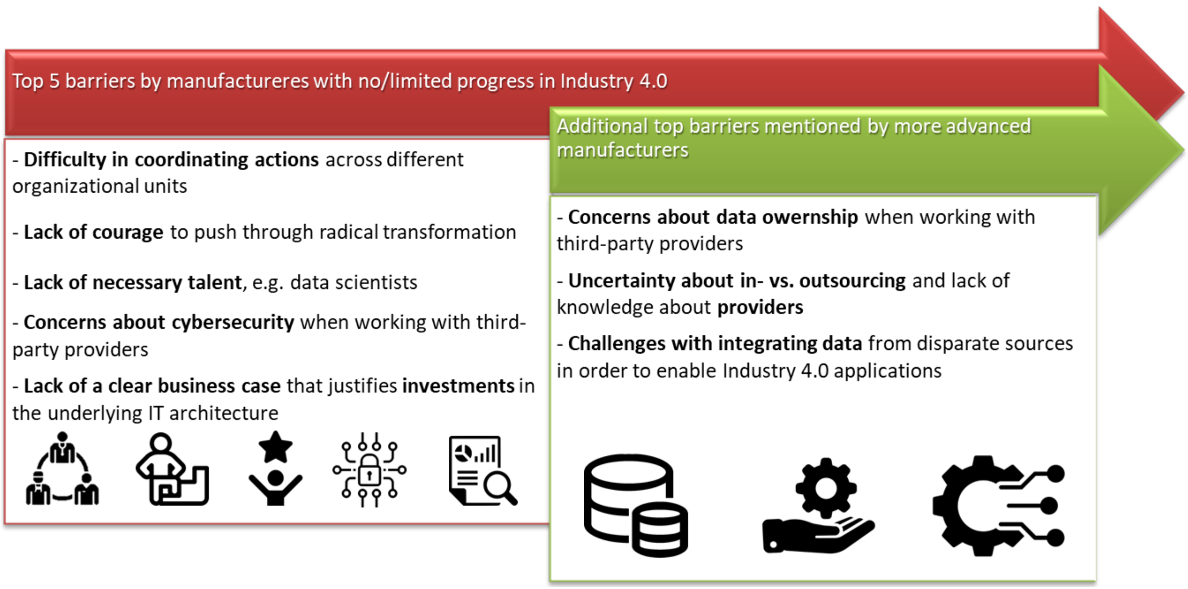

Figure 2.8: Top barriers prior to and during adoption, adapted from McKinsey Digital (2016).

Six Sigma, one is already implementing the basics for the Industry 4.0-philosophy. On the other hand, by looking at the existing data you can implement Industry 4.0 more effectively through addressing quality-related challenges. These simple adjustments (i.e. perspectives) make the collusion of both favorable, as you can use utilize the best of both worlds. Moreover, this combined way of improving existing processes shift the attention from challenges to opportunities.

One methodology that is especially suitable for improvement studies and already widely enrolled across the manufacturing industry, is the Six Sigma DMAIC method. The DMAIC-procedure, as shown in Figure 2.9, targets large or recurring problems within the organization. Effective industry 4.0 adoption also involves the procedure of finding the bottlenecks and addressing them first (Liere-Netheler *et al.*, 2018), making it a good fit with the problem solving nature of the DMAIC.

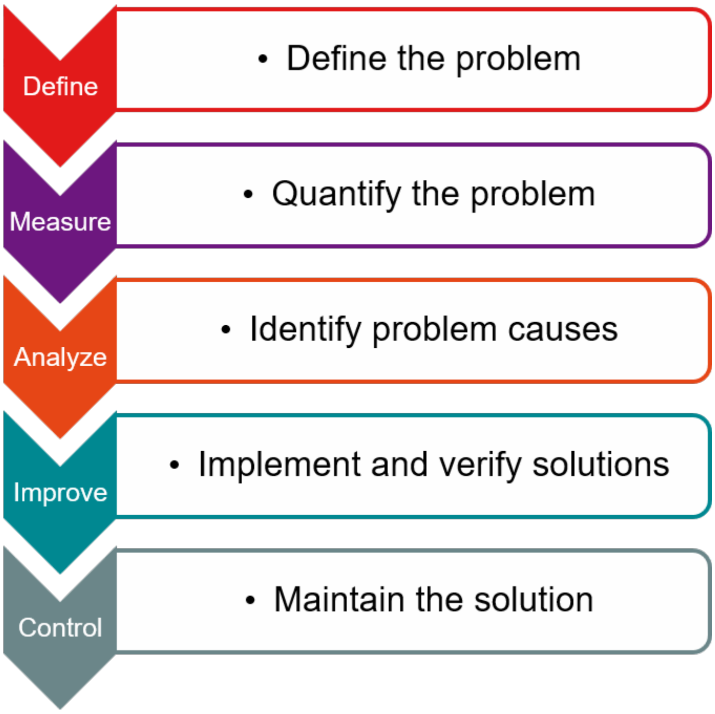

Figure 2.9: The five stages of the DMAIC improvement process.

At first, the problem must be **defined**. In current practice, this refers to describing the problem. For example, a customer files a complaint about a delivered product. The D-stage is then dedicated to describing the malfunction reported. In the case of Industry 4.0-implemention this first step will not only describe the problem, but also the intention of changing. As the problem is not a clear one, the objective is. An organization might consider Industry 4.0 adoption to boost performance or just to maintain its competitive advantage. This step is identical to the common 'define'-stage, because it focuses both on identifying the nature of the project.

The subsequent step is less straightforward in the case of Industry 4.0-implementation (Soltan and Mostafa, 2015). In a regular employment, the **measurement** stage is solely focused on collecting data and understanding the overlay. Something similar was identified in subsection 2.1.3, where the initial focus lays on describing the overlay after which this overarching body is used to categorize the different indicators. A similar approach can be applied to the Industry 4.0-context, where in the 'measurement'-stage, you describe in what context the technology is introduced.

Then the results are prone to evaluation (Soltan and Mostafa, 2015). Usually, one starts to assess the data obtained or dives into the root causes of the earlier observed and reported problem. In the context of Industry 4.0 this analyzing step is merely dedicated to finding the existing pain points in operations. First of all, you want to know what causes inefficiency to find a technology that effectively targets that issue. Then you want to apply a digital driven solution to accurately capture what you found artificially. Finally, data is obtained throughout the analyzing stage, allowing a thought-out improvement stage. The **analyzing** stage is, similar to the regular approach, the most time-intensive stage for Industry 4.0 implementation.

Following the results from the analyzing-stage, is the actual **improvement** of the system through implementation of a solution. With respect to Industry 4.0, this means that a data-driven technology provided insights into ever-occurring inefficiencies, like the continuous lack of storage. With the data-driven approach, one can look at multiple solutions now, like efficient storage planning using the data or a more radical approach that involves capacity expansion.

With all the dedication put into a good solution, the final stage comprises of **maintaining** the solution. (Soltan and Mostafa, 2015) is one of the key aspects in a solution-maintaining strategy. You assess the applicability of a solution and try to improve its performance even further by continuously assessing the effectiveness of the solution.

After careful execution of the implementation program, according to the DMAIC structure, substantial improvements are made. Crnjac *et al.* (2017) describes describes the potential of this integration by delineating differences between the existing industry (3.0) and the coming industry (4.0) using a few keywords, depicted in Figure 2.10. Currently, manufacturers are mainly targeting their manufacturing process as their key drivers. With the introduction of smart products, i.e. products that collect data, the context shifts towards the product lifetime as the product becomes an essential element for further development. Also the shift from planning to acting will contribute to the reduction of waste, enhancing the lean manufacturing philosophy to a smart manufacturing philosophy.

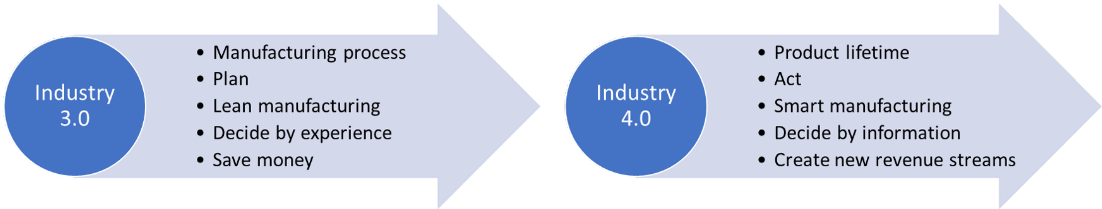

Figure 2.10: Most significant changes compared to existing manufacturing industry, inspired by Crnjac *et al.* (2017).

2.3. Actual implementation

Despite the majority of the industry does not follow the digital transformation trends as of yet, some companies have made the shift and with success Manavalan and Jayakrishna (2019)! Regardless of the success, a lot can be learned from those who took the jump from Industry 3.0 to Industry 4.0-based manufacturing.

Especially the case studies described in the literature are of upmost value, because of the implementation challenges faced and the found applicability of particular technologies to particular situations. For each case study it was checked what kind of technology was applied, in what context (i.e. type of factory and business process), considerations, trade-offs and what benefits were obtained. This large amount of information provides a solid basis for future Industry 4.0-adopters in their decision-making process.

From these case studies, and including some theory-based articles, implementation stages are derived. Each implementation process comprises of multiple subsequent actions which all add value to the total. Identifying which stages were required help the development of an implementation framework.

Finally, a conceptualization of the holistic nature of Industry 4.0 is needed. Up to this point, a large amount of different terms were introduced, sometimes overlapping each other, and sometimes contradicting each other. To establish a common ground, practitioners developed a model, RAMI, to clarify what technologies and layers exist in the Industry 4.0.

2.3.1. Case studies

Based on the literature study described at the start of this chapter, 14 distinctive case studies dedicated to supply & planning were found. For each of these case studies it was noted what technology or technologies were introduced through the case study. Besides the enabling technology (i.e. from Figure 2.5), also the actual technology was mentioned to provide examples and options for businesses to follow.

Only 1 of the case studies (7%) used *simulation* as an enabling technology for further development. The main focus of Belli *et al.* (2019) was improving the production planning process by reducing errors. SmartPlanner, the software which was deployed, had to cooperate with existing software, logic and models. Thus the main consideration was modularity and connection with the existing Enterprise Resource Planning (ERP) system, which was found by obtaining most of the data by human observation rather than automatic data collection. In a second stage, the introduction of IoT was able to overcome the challenges associated with human observation. Essential benefits of this system are: up to date visible data, digital traceability, and -above all- the error-reduction.

Another, relatively unused enabling technology is *Business Intelligence* along with *Blockchain*, with only one mention (7%) in all case studies. Arumugam *et al.* (2018) describes the use of a business intelligence-blockchain platform in the so-called 'Architecture integrated smart logistics', where the supply & demand logistics of a food chain is controlled. In the case study -focused on end-to-end integration- transparancy, traceability, and acountability are considered to be the Critical Success Factors (CSF's) (i.e. goals). The major considerations taken in this case study relate to the smart contracts of the blockchain technology for which it was hard to pre-define exceptions that could arise causing the contract to not be fulfilled. The study's applicability is limited due to the fact that it has not been tested.

The third technology found in case studies was the use of *IoT*, found in 3 separate case studies (20%). In the first study, an IoT architecture was used to perform condition and quality control, increase planning and scheduling efficiency, and to improve information visibility (Yang *et al.*, 2019). To test the idea, a virtual machine network with many different technologies was created. Customization was one of the biggest burdens when considering the topology of the IoT architecture. There were different data segments (i.e. quality control and scheduling efficiency) which require a completely different IoT sensors, therefore preferring sensors that are able to capture different types of data. In the end they chose to just go for the 'measure-it-all' approach and had to implement a large amount of sensors. The large amount of incoming data required sophisticated data algorithms to effectively downsize the data to meet the needs.

Lee (2019) targeted their key supply of an automotive batch process by introducing an IoT structure (called ECminer) to measure its cycle time, Work in Progress (WIP) and throughput (TH). Using this structure, they established an end-to-end type of integration with their suppliers, increasing the efficacy and efficiency of their supply. However, data sharing was found to be a major issue. Only with a mutual contract, they agreed on providing data to the suppliers to avoid future problems.

The final IoT structure was introduced by Rezaei *et al.* (2017), who improved the production planning by using an IoT-based real time framework. The aim of this study was to minimize costs and to maximize agility and reliability, but with cost effectiveness. The only way of keeping IoT relatively cheap, was by addressing only 3 KPI's and leaving out the others for future plans. Eventually this strategy based decision making increased the performance of the KPI's

Automatic Identification and data collection (AIDC) which involve technologies like bar codes, RFID's and other 'evolved' sensors covered 27% (4) of all case studies. In the selection of case studies, Lee *et al.* (2012) was the first to use RFID tags. In the Garment industry they faced problems with resource allocation due to the high amount of machinery that use the materials at a different time at a different rate. By using RFID's, Lee *et al.* (2012) reduced the variance between expected and actual resource utilization, with the side benefit of standardizing the full resource process. Instead of enhancing the existing Warehouse Management System (WMS), they introduced fuzzy logic to make sense of the incoming RFID-data. By doing so, they enhanced the overall visibility of resources within the system. However, it is considered hard to find what data must be measured, and the final topology was not an efficient one, yet really promising.

Reaidy *et al.* (2015) targets the end-to-end integration with its AIDC strategy. Their negotiation protocol utilize a collaborative warehouse at its maximum by scheduling depending on dynamic changes (by AIDC). The main goal of this negotiation protocol is to increase the responsiveness and agility of said collaborative warehouse. Through development, the team found it had to make some major trade-offs in order to get the system running; Return on Investment, manager trust and guaranteed performance were the challenges they had to abandon in the developed system. However, the benefits of reducing warehouse delays and costs were significant and a good indicator for future success.

One divergent case study is found in the smart logistics management system by Chong *et al.* (2018). In their case study, the team tests a full architecture for logistics management, measuring ingoing and outgoing materials by means of AIDC. The main purpose of this system is to obtain real-time data about the status of stocks at the different companies involved in the supply chain. According to the VDMA toolbox for industry 4.0, Chong *et al.* (2018) developed a system that is moderately sophisticated in terms of Industry 4.0.

In a soap factory with multiple production lines and conveyor belts, Wang *et al.* (2016b) developed an intelligent decision making and negotiation agent utilizing RFID. Increase of efficiency, profitability, and transparency are just a few of the KPI's addressed throughout the implementation process. In doing so, physical assets (i.e. RFID's) must work together to establish the required 'smart' network. However, having that many connected devices immediately results into the first implication; that of bandwidth. So much data has to flow through the wireless sensor networks (WSN's) that only the ones that process data at a high speed were suitable. Figure 2.11 provides an overview of the interconnected system of Wang *et al.* (2016b) working collaboratively to select the most optimal production order. Subsequently, one could see that such systems do not rely on just AIDC or IoT, but often some cloud and terminal layer are required as well. *Cloud technology*, as one would expect, was used in most of the case studies (8 resulting in 53%). Others like Yang *et al.* (2019); Reaidy *et al.* (2015); Arumugam *et al.* (2018); Lee (2019); Chong *et al.* (2018) also had some sort of cloud technology in place, but not as prominent as in the study by Wang *et al.* (2016a). In a batch factory for multiple different products, Wang *et al.* (2016a) created a closed-loop conveying system by using algorithms and a cloud. The main focus is the prevention of dead-locks inside the conveying system using smart algorithms, rather than increasing the buffers. In the end, the study was concluded to be effective, since the batch process changed to a semi-continuous process while maintaining the ability of product customization.

Accorsi *et al.* (2018) developed a procurement and transport decision-support platform for the import and export of food. The main purpose of this cloud solution was to reduce travelling (time, number of shipments, and costs) via the use of smart algorithms. One of the biggest challenges here was the missing data from particular parties as the required degree of end-to-end integration was not obtained yet. Consequently, the team had to use coding to 'guess' the missing data entries, thus decreasing the reliability of the technology. However, using this technology as a simulation induced insights into what needs to be improved in existing operations.

In the candy packaging line of Chen *et al.* (2017), a cloud system was developed for improving the performance-, availability-, qualified-, and Overall Equipment Effectiveness (OEE)-ratios. New 'intelligent' equipment was required to coope with the significant data flows, namely configurable controllers and self-reconfigurable. With the new equipment, and in accordance with the developed cloud system, the team increased the ratios significantly, of which OEE was the most considerable (from 42% to 82%).

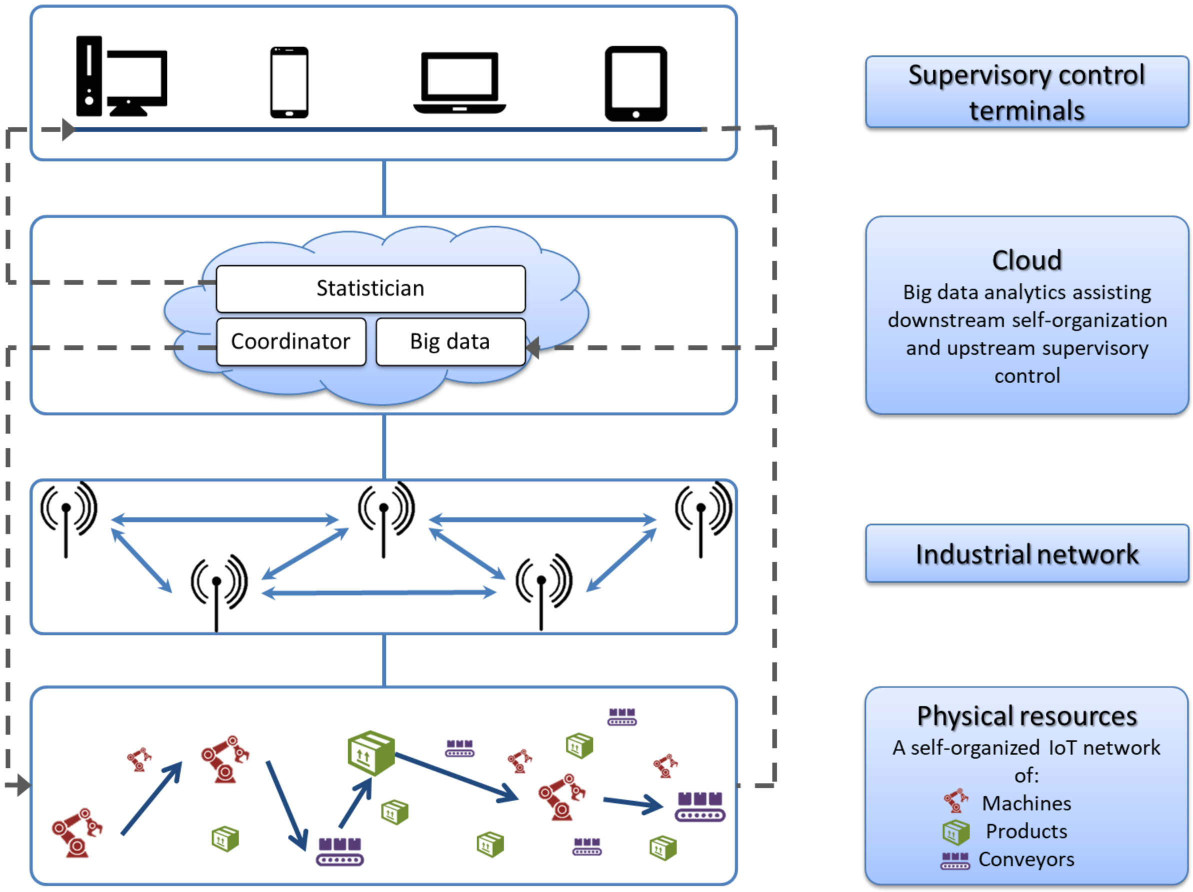

Figure 2.11: An example case study, adapted from Wang *et al.* (2016b).

The final and largest category of technologies found in the case studies, was *(big) data analytics*. A vast 60% (9 cases) contained data processing techniques. The case studies treated so far, Belli *et al.* (2019); Wang *et al.* (2016a); Lee *et al.* (2012); Chen *et al.* (2017); Lee (2019); Wang *et al.* (2016b); Accorsi *et al.* (2018), do not require a second explanation. The remaining use cases are found in Zheng *et al.* (2019) and Do Chung *et al.* (2018). Zheng *et al.* (2019) applied a two-stage supply algorithm to define the production order for a batch process with different machines. Sharing demand information with the suppliers was considered to be an essential part of the supply algorithm, thus requiring some form of end-to-end integration and making internal business information public. Although it was not preferred to share this information, the technology increased profits by 5 to 17%.

The case study of Do Chung *et al.* (2018) is investigated for its production order algorithm. They looked into an additive manufacturing site where multiple 3D-printers are located that produce separately. To make effective use of the 3D-printers in place, the algorithm determines the fastest production order. Moreover, they introduced the collaboration between different companies, allowing different manufacturers to make use of the -otherwise stationary- 3D-printers. Although the complexity increased significantly, the team enhanced the dynamics of the supply chain while remaining flexible regarding changes and uncertainties.

2.3.2. Implementation stages

Different types of implementation articles were found through the strategy adopted. Some researchers used older literature in order to combine ideas and technologies (Arnold and Voigt, 2019), while others reiterate their findings in an actual case study (Chen *et al.*, 2017). Also the application portfolio is widespread, where one focuses solely on Small and Medium Enterprises (SME's) (Chaopaisarn and Woschank, 2019) and another on the domain of Just in Time (JIT) manufacturing (Xu and Hua, 2017). Combining all this information gives an idea about the subjects covered so far.

The literature captures a wide range of implementations, as shown with the variety of case studies in subsection 2.3.1. Consequently, the literature tends to describe the implementation plan by using three different structures. The first being the integration approach, shown in Figure 2.2 at the start of this chapter. Three levels of integration (i.e. horizontal, vertical and end-to-end) are often buzz-words to describe the degree of industry 4.0-implementation. A vertical integrated company controls its inner manufacturing processes using digital solutions, but it is unclear to what degree they do this. Similarly, the horizontal integrated companies are supposedly exchanging information through digital solution, however, to what extent is unknown.

To know to which degree digital transformation was applied, a second implementation structure is found in complexity level of implementation model by Frank *et al.* (2019). Figure 2.12 shows what type of technologies are associated with what stage of industry 4.0 implementation. Moreover, this model subdivides the front-end technologies (smart manufacturing, smart products, smart working and smart supply-chain) that describe the technology's purpose versus the base technologies that simply provide the basis for innovation. Apparently the use of cloud services is perceived to be an absolute minimum (stage 1) for companies to advance into the industry 4.0-philosophy. Implementation of some IoT technology to increase traceability and energy monitoring is considered an absolute minimum to advance in Industry 4.0. As soon as Big Data and analysis, like AI, M2M, and additive manufacturing, are introduced, smart manufacturing reaches the sophisticated stage of Industry 4.0-adoption. However, this still does not indicate how the integration levels are aligned with technology introduction.

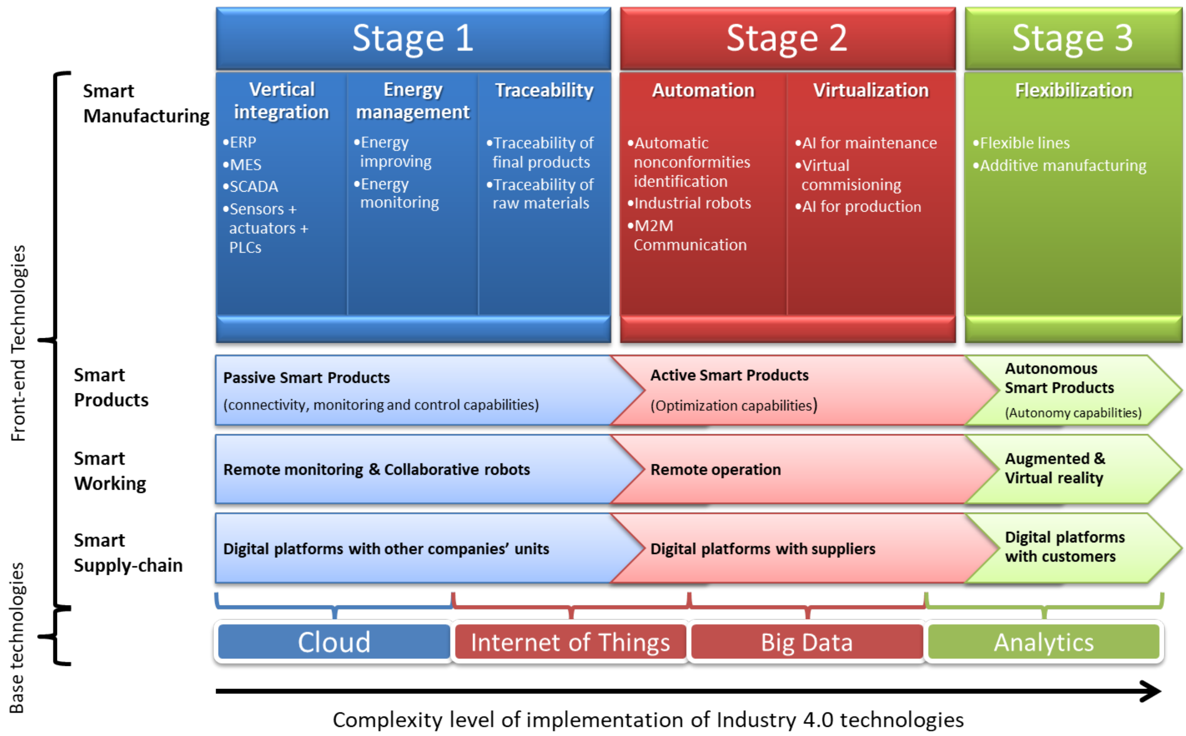

Figure 2.12: The different technologies visualized by increasing complexity as well as the corresponding category, adapted from Frank *et al.* (2019).

Through the implementation phase, Chaopaisarn and Woschank (2019) found the third implementation model by specifying three stages of implementation of Smart Supply Chain Management (SSCM), shown in Figure 3.1. The Local Application Model (LAM) comes first and serves as a stage in which the company uses smart sensors and RFID's for the first time, with the sole purpose of saving costs. Second comes the Isolated-system Application Model (IAM) where the first algorithms and a general architecture are introduced. Finally, the Smart Supply-chain Application Model (SSAM) starts and focuses on smart supply chain integration and collaboration with other companies. All though Chaopaisarn and Woschank (2019) mentions the specific use of SME's for his findings, supply chains for larger corporations are in essence similar.

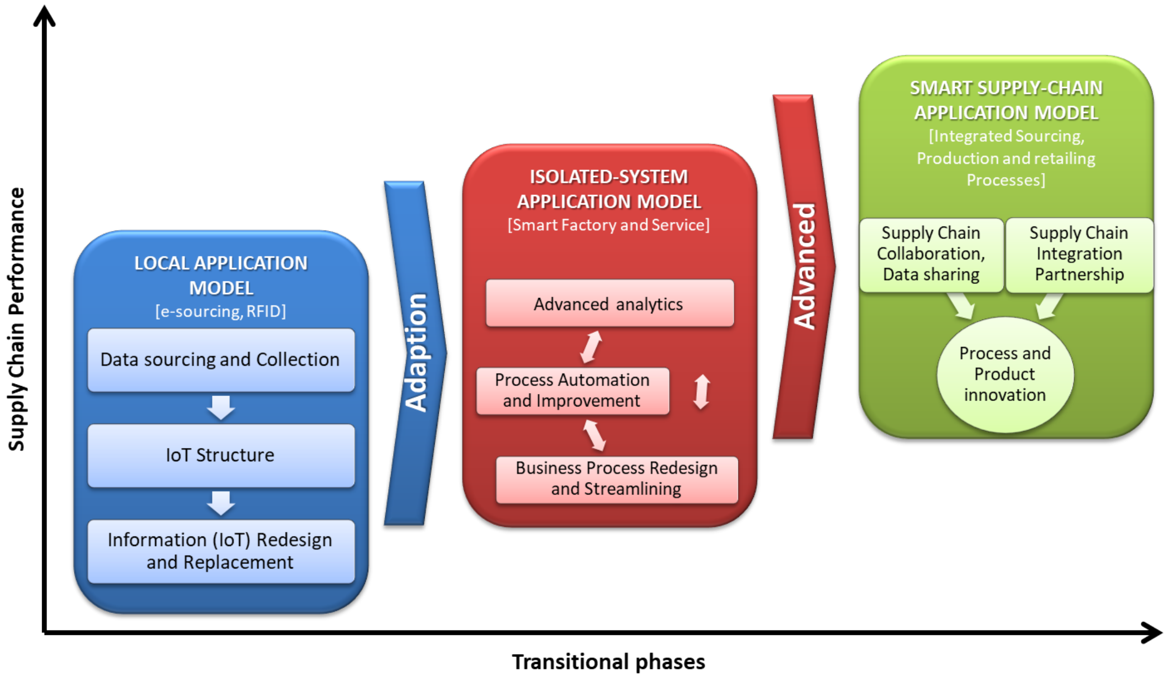

Figure 2.13: The implementation phases as adapted from Chaopaisarn and Woschank (2019).

Implementation of innovations like these will often take place on many different levels within the company both in terms of tangible and intangible items. To streamline the implementation process, Osterrieder *et al.* (2019) and Wang *et al.* (2016a) define 4 layers that will be touched upon during the implementation process. The four layers are; physical layer, e.g. machinery and equipment, the data layer, e.g. big data from all sensors, the cloud & intelligence layer, e.g. data analytics, and the control layer where the decisions are made. This whole combination of layers is often referred to as a Cyber-Physical System (CPS) (Karabegovic *et al.*, 2020), as shown in Table 2.2.

Despite there are three different models that identify the implementation progress of a company, there is no such thing as an implementation framework. The case studies from subsection 2.3.1 also provide very limited information about the steps undertaken, other than the trade-offs and final results shown. For a company to overcome the adoption barriers mentioned in subsection 2.2.2 more than the overview of just a few technologies in subsequent order is needed. It became apparent using the case studies that preliminary research is compulsory to find appropriate applications (i.e. business process) in which the technologies can actually improve the business. If this preliminary research is not executed, it is likely that technologies are put on random applications, thus creating an ineffective industry 4.0-portfolio (Sjödin *et al.*, 2018).

To understand what must be included into an implementation model, we take a look at the work by Nilsen (2015). According to Nilsen (2015) early implementation research is empirically driven and does not always pay attention to the theoretical underpinnings of implementation. This is clearly the case for the case studies, while exactly the opposite holds true for aforementioned models. Nilsen (2015) used three overarching aims to describe the applicability of a model: (I) describing and/or guiding the process of translating research into practice, (II) Understanding or explaining what influences implementation outcomes, and (III) evaluating implementation. Perspectives II and III are widely covered in the existing literature while I, knowing the bridge between practice and research, is a rather neglected concept.

Nilsen (2015) puts emphasis on the context in which the so-called process model (i.e. perspective I) is developed. Thus, indicating that a process model must be clear about the context in which it applies, and in accordance with the used research. Moreover, planning is emphasized as a key enabler in the whole implementation model, especially in the early stage of implementation. Many of the models investigated by Nilsen (2015) have a dedicated planning process at the very start to proceed step-wise in an orderly and linear fashion.

Someone particularly good at the development of an implementation model is Aitken *et al.* (2004). In their handbook they describe the full employment of an improving quality model through analysis of variables. In a model of just 10 steps, Aitken *et al.* (2004) reaches a plan for continuous quality improvement. Figure 2.14 shows the consecutive steps for defining, identifying, analyzing, improving and evaluating the issue in one compressed plan. By careful examination of the issues at hand, including analyzing the key variables, issues related to ineffective measures are prevented. The subsequent stages where an initial solution is reviewed allows to check whether the proposed interference actually does what it is supposed to do. Finally, the system is improved and subsequently the quality is improved.

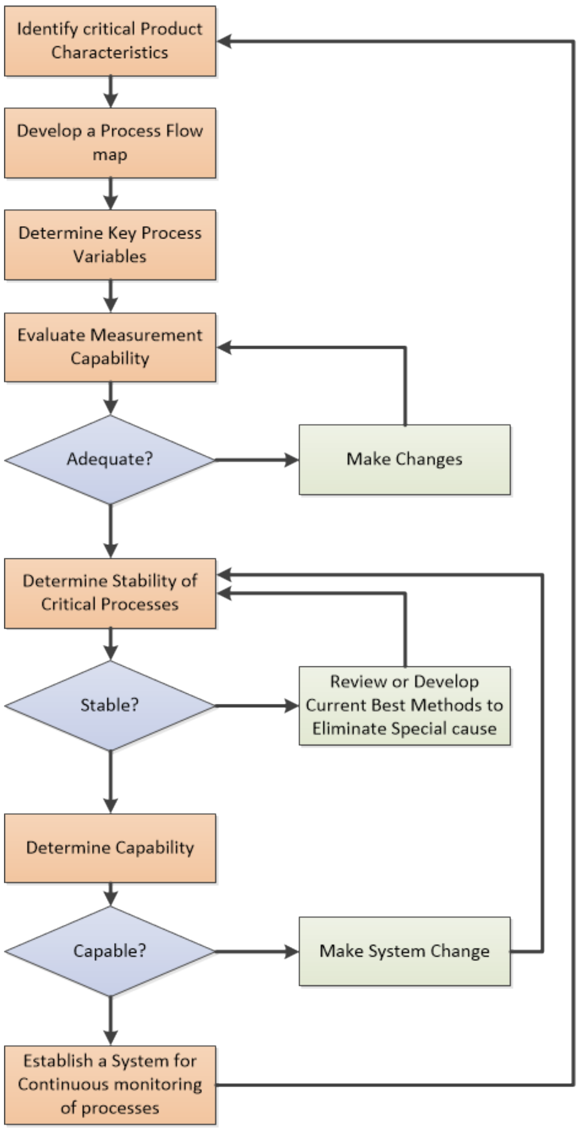

Figure 2.14: A plan for Continuous Quality Improvement, adapted from Aitken *et al.* (2004).

Overlap between the quality improvement model and the observed industry 4.0 implementation is gigantic. In every stage of the quality improvement model, a similar approach (intentionally or not) is taken according to the research assessed. Furthermore, the existing research provide a perfect framework with solutions to be incorporated into the ”system change”-stage of the quality improvement model. Therefore serving as a perfect basis for further development of the implementation model.

2.3.3. RAMI

The four layers of CPS, indicated in Table 2.2, provided a solid basis to understand how different technologies are interconnected within a smart factory. However, for actual implementation, this understanding is rather limited. CPS is limited to the 'front' technologies which provide the actual novelty which the companies are after. Reference Architectural Model Industrie 4.0 (RAMI 4.0) provides, as the name suggests, a structured model to understand the different layers responsible for the Industry 4.0-implementation. RAMI 4.0 is a 3-D model showing how to approach the issue of Industry 4.0 in a structured manner (Schweichhart, 2019), shown in Figure 2.15.

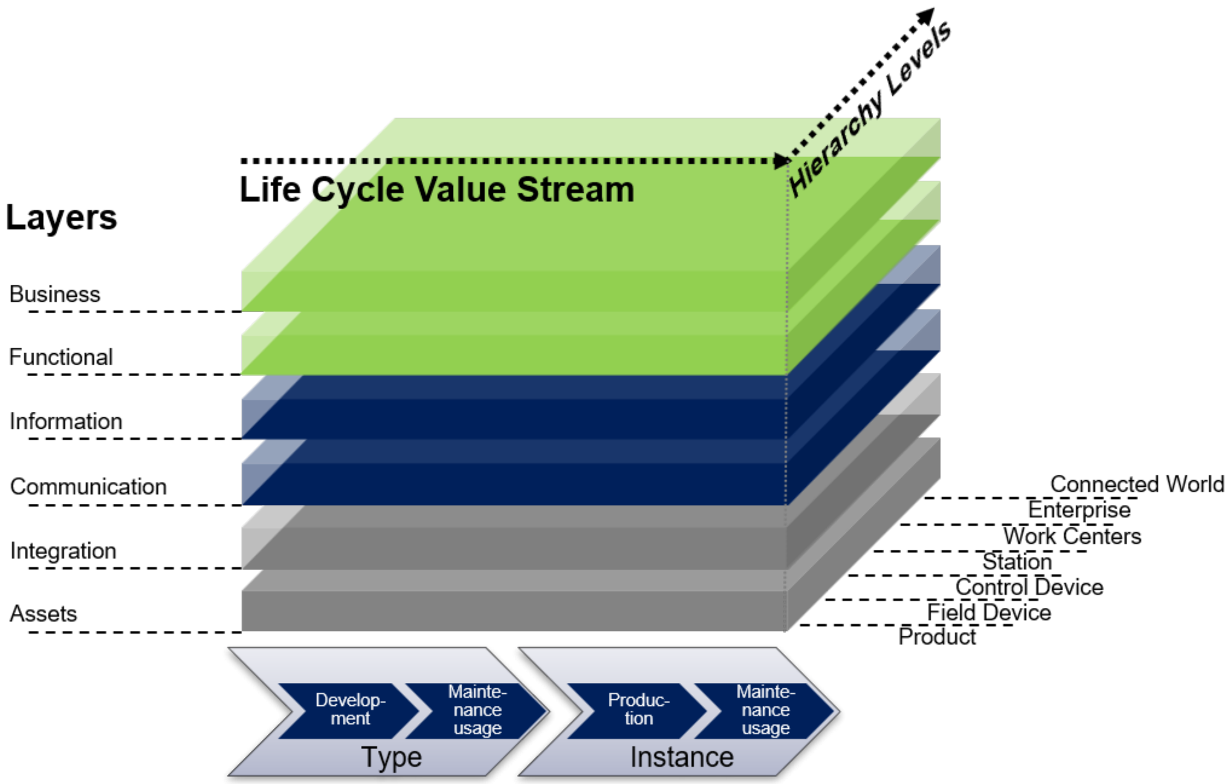

Figure 2.15: Reference Architectural Model Industrie 4.0 (RAMI 4.0) adapted from Schweichhart (2019).

The first dimension of the RAMI model is the ”Hierarchy level”. This dimension differs significantly compared to the classical 'Industry 3.0' fashioned hierarchy. In the current situation, hardware like field devices, control devices, and stations are operated in an hierarchical manner (Schweichhart, 2019). This applies especially to factories that run on many different assets (e.g. valves, pumps, etc.). These assets are all combined and connected in a PLC, which on its turn is connected with all other PLC's to a SCADA system for that particular factory. The SCADA systems of the factories combined is then integrated into a supervisory control for a plant manager, showing a truly hierarchical system (Uslar and Hanna, 2018). However, in the case of Industry 4.0, these assets are all interconnected to different pieces of hardware depending on its applicability. To understand how all assets are interconnected while still maintaining an useful and clear overview, RAMI 4.0 subdivided the hardware into the existing hierarchical levels which can then be used to draw the connections amongst them.

"Life Cycle Value Stream" is the second dimension of the RAMI model and refers to the product's life cycle. A product is first developed (i.e. prototype, simulation, construction) before it is introduced into the market (Schweichhart, 2019). Subsequently follows the preparation for production, meaning that software is updated, instruction manuals are ready, and enabling processes like maintenance are aligned accordingly. After defining "type", "instance" starts where actual production takes place. Important aspects in this life cycle is the introduction of data, like type of product and serial number to understand unique identifiers of the product. Similar to the "type" stage, enabling business processes like service, maintenance and recycling are critical aspects of the product's lifecycle.

A final dimension is found in the architectural layer, similar to that of the CPS. In the RAMI model, 6 distinctive layers for describing an Industry 4.0-architecture are identified (Schweichhart, 2019). At the bottom, "assets" describe the physical things in the real world, like computer devices, valves and raw materials. To collect data from the physical world and get it into a digital world, we need the integration layer, that enables transition from real to digital world. Communication follows directly after and implies the access to information through connection. Information is the subsequent data layer on which the necessary data is available, e.g. database or cloud system. Using this data, we enter the functional layer on which algorithms and data analysis form the basis for decision making. At the very top are the Business Processes related to the other two dimensions forming the connection between data utilization in both the Life Cycle Value Stream and Hierarchy Levels.

2.4. Practical background

As indicated in chapter 1, the introduction of this thesis, research and practice do not connect well. Within the literature study of this chapter it was investigated what kind of advancements the industry can make by adopting industry 4.0 alike technologies, how these align with the existing business practices, and how to implement said technologies. However, the identified adoption barriers specify the misfit between opportunity (i.e. research & innovation) and the imposed risk (practice). To better understand the difference between them and to reduce the gap between them, we must further evaluate the practical background.

In the practical background we are after three major constructs for the implementation framework. By interviewing different European practitioners, all in a different field, we can understand what hampers real adoption complementary to the adoption barriers of subsection 2.2.2. With the results from this interviewing session, a GAP analysis between the theoretical approach and practical approach is obtained, thus strengthening the constructs of the implementation model.

2.4.1. Interviewing methodology

In total, 8 interviews were conducted from interviewees that exercise their job within the European union, working at 6 different companies, and having completely different job descriptions ranging from supply chain managers to Industry 4.0 implementation managers. Their names and companies are known by the research team, but are kept secret in terms with the Code of Ethics of the TU Delft.

The wide variety of expertise and the high average working experience (>15 years) allowed to dive deep into the subjects throughout the interview. The limited time (i.e. 40 minutes averagely) however, required a particular interviewing strategy. Qualitative semi-structured questioning was the method to persuit, because this facilitated an open discussion, where subsequent questions were asked depending on the interviewees' answer. By semi-structuring the questions, it was ensured that all important topics were addressed. Especially the difference in background, like supply chain (i.e. procurement, operations), consultancy (i.e. implementation), and technology require an easy-going flow of questioning, simply because some terms had to be explained in the context of the practitioners' expertise.

Although about 15 questions were prepared prior to the interview, only a few of them were considered critical and are required for the support of the implementation model. These essential questions follow from the three main backbones of the interview. These three are: (I) Existing bottlenecks in the manufacturing environment, (II) KPI's selection through implementation, and (III) Implementation approach. The order of the questions was based on the interviewees' expertise. Typically we start with the topic closely related to its expertise, e.g. existing bottlenecks for operations managers and implementation approach for consultancy experts. From this starting question on, we work through the other topics step-by-step.

Existing bottlenecks in factories are considered to be good indicators for what challenges to target first. Practitioners have experienced many issues with regards to manufacturing throughout their career, which empowers them to come up with a top 3 of operations-related bottlenecks. This is valuable information through the development of the implementation model as it clearly shows in what kind of environments and for what type of challenges the model will get used.

KPI's selection is the result of subsection 2.1.3, where critical parameters were selected through models like SCOR and BSC. These models are identifiers for the existing business processes and provide valuable information about a company's performance. Currently, there are over 4000 'official' KPI's, making it nearly impossible for managers to monitor everything (Gordon, 2011). Knowing commonly used KPI's by the practitioners, increased with the applicability to the Industry 4.0-philosophy, significantly helps to develop a framework in line with today's standards aligned with tomorrow's solutions.

Implementation approach is obviously a key item in the construction of an implementation model. Especially the consultants who have been implementing Industry 4.0-related technologies at multiple companies, also being the main advisory organ for many governments, contributed significantly to the establishment of the implementation stages. Moreover, the literature lacks good and practical-oriented implementation model, thus making this item the main source of information in terms of implementation practices.

A final -yet less important- element that was addressed in the semi-structured interview is the topic about implementation challenges. Although some articles already describe the adoption barriers, an extra verification is obtained through the interviews. The identified adoption barriers are - amongst others - the cause for this need of the implementation framework and serve an essential role in the construction of it. When creating the implementation frameworks, we want to overcome barriers that typically apply in the supply & planning domain.

2.4.2. Results

Seven completely different and interesting interviews were conducted between March 2020 and April 2020 amidst the global COVID-19 pandemic. Via digital telecommunication tools like Skype and Microsoft Teams it was possible to record all the interviews - with permission of the interviewee. Each interview was transcribed manually to obtain a text-version of each interview. Subsequently the text-versions were reviewed and all chatter was removed. Then the information regarding the main topics from subsection 2.4.1 were extracted into a general file devoted to all interviews combined. After all interviews were reviewed like this, the answers to each topic were subtracted and collected into a table or roadmaps (i.e. in case of the implementation approach).

At first, the answers to existing bottlenecks (I) were collected in Table 2.3. In total, seven different answers were given, of which 3 were mentioned multiple times. Especially the quality of raw materials is considered to hamper current operations performance. Both procurement and production need to know what quality of raw material is coming in and what quality must be purchased, however, this is not always the case. The lack of standardization and the large dependency on experience are also considered as significant issues for further growth, where Industry 4.0 might tap into. The remaining 4; visibility of the supply chain, production planning, stock levels, and capacity are somewhat interfering within the operations performance, but not as significant as the top 3.

Discussing element (II) KPI's selection with the interviewees resulted in interesting conversations. One of the interviewees mentioned that there was a consistent misuse of KPI's within the industry. Particular managers used reference levels adjusted to their own system, thus increasing their own KPI performance (up to 90+%). While if they had used the right reference levels, KPI's dropped to 40-50 %, thereby hiding that significant improvements could have been made. This clearly indicated that us-

Rank	Existing bottlenecks	Freq.	Context
1	Knowing the minimum quality of raw materials	3	Procurement and production
2	Lack of common tools; no standardization	2	Production planning
2	Lot of experience required for efficient planning	2	Production planning
3	Visibility of the supply chain	1	Procurement and production planning
3	Production planning efficiency	1	Procurement
3	Keeping safe stock level versus flexibility	1	Procurement
3	Aligning capacity to customer demand	1	Production planning

Table 2.3: A list of recurring bottlenecks of a supply & planning environment.

ing KPI's as the basis for Industry 4.0-implementation (i.e. to effectively address the under-performing processes) was not the right track. However, using KPI's throughout the Industry 4.0-implementation will help managers to indicate how business has changed.

Useful KPI's according to the interviewees are shown in Table 2.4. Quite obvious is the first KPI entry; efficiency. Within operations, and production planning in particular, it is efficiency that serves a significant portion of the profit made. Quality, downtime and savings follow right after. Quality and downtime are indicators that are also part of one's operations efficiency. If the quality is incorrect; new production runs are intercalated. For downtime this holds true as well; every minute that the operations is not working accordingly reduces the overall efficiency. The remaining KPI's; environment, perfect order rate, price over volume, cost avoidance and OEE are completely distinct indicators, but all add a bit information in terms of how the process is performing.

Rank	Key Performance Indicator	Freq.	Context
1	Efficiency	3	Production planning
2	Quality	2	Production
2	Downtime; production capacity	2	Production planning
2	Savings	2	Procurement
3	Environmental (e.g. carbon footprint, energy efficiency)	1	Production planning
3	Perfect order rate	1	Production
3	Price over volume of raw materials	1	Procurement
3	Cost avoidance	1	Procurement
3	Overall equipment effectiveness (OEE)	1	Production planning

Table 2.4: A list of Key Performance Indicators that are generally adopted during digital transformation in a supply & planning environment.

The third element (III) implementation approach was addressed with more care. On average, the time spent running through the different implementation stages took over 60 % of the time. Subsequently, multiple implementation strategies were obtained that all had a different focus and different steps. However, the order of the actions kept coming back in a similar fashion, therefore enabling the construction of Figure 2.16 which combines the descriptions of all the interviewees. As can be seen in Figure 2.16, only 6 strategies were obtained. Due to the lack of fundamental knowledge about Industry 4.0 and the corresponding innovations it was not possible to run through this process with two of the interviewees.

The remaining six show that some practitioners follow a quite similar approach, while others clearly differentiate themselves by performing different actions. For example, the second strategy starts with a clear construct of an overview to define the existing infrastructure. Subsequently, he continuous in digitizing the administrative tasks, rather than jumping straight into the pain points. Another noteworthy result is the consistent return of action 7; "set goals and determine KPI's" along with action 10; "applying sensors to measure the data required".

Step:	1	2	3	4	5	6	7	8	9	10	11	12	13
Strategy	Create an overview of your capacity and infrastructure	Define pain points, understand these including their solutions	Define which administrative tasks can be done digitally, use a standardized tool/option.	Put a network in place that is capable of connecting OT with IT, to gather most of the relevant data.	Align data already available with processes in order to make them uniform. Simplification and harmonization are key.	Determine how the data can be collected and start collecting data in an easy way at this point. Already think about how this data will be reported in the future.	Set goals and determine your KPI's depending on your pain points. *Think big, act small.*	Focus on similarities. 80% of the value is probably in 80% of the similarities.	Make a business case.	Apply Sensors to measure the data required for your KPI's .	Apply models that process the data and can be used for improvements/ analyze the data.	Review proof of concept	Reiterate. *Fail fast; but fail safe.*
1							X			X	X	X	X
2	X		X		X	X	X			X			X
3				X	X	X	X			X			X
4		X				X	X		X	X	X		
5		X					X	X		X			X
6		X		X	X	X			X	X			X

Figure 2.16: The 6 different implementation strategies obtained through the interviews.

One concern that arose during the interview analysis is the dominant nature of 'sensors' and the lack of introduction of other technologies like Cloud, algorithms and robotics. The cause for this is assumed to be two-fold. Most of the practitioners have established Industry 4.0-solutions based on existing architectures, like cloud systems that were already used for the daily tasks (e.g. Office 365). The second being the lack of maturity within the implementation cases, causing them to focus on the very basis at first. Both causes can be supported in the actual implementation model where an iterative process will consecutively mature the digital transformation process, thus disregarding the need for a degree of maturity at very first implementation loop.

Altogether, the 13 steps shown in Figure 2.16 provide a solid basis for further development, as these are continuously put into practice, and with success! However, we have put these steps together based on the perception and context given in the interviews. When constructing the framework, this context might change thus making particular steps overlap, such as the combination of the two steps is considered more valuable than executing them separately.

The final side-element that was checked through the interviews is the list of challenges perceived when performing digital transformation. The most prominent challenge, being mentioned in 75% of the interviews is the term 'people management'. Other than in subsection 2.2.2 which mentions the difficulty in coordinating actions, the practitioners clearly observe the human dynamics within a company as one of the key challenges, therefore also being the largest burden for companies to advance in the Industry 4.0-philosophy. Especially the aging population, who are not familiar with the use of these fast changing technologies, have difficulties in adopting them.

Other significant challenges are found in the maturity of Industry 4.0, the chaos of data available and the lack of a standardized (i.e. one-size-fits-all) approach. The combination of maturity and the standardized approach indicate that a lot more research needs to be done in order to get more practitioners in the field of Industry 4.0, as well as to increase the adoption rate of manufacturing businesses. The chaos of data taps into a completely different world, expressing the huge existence of (historic) data, but it being truly chaotic and difficult to use. In the ideal situation, the available historic data is collected, organized and used to further enhance the capabilities of the digital transformation. However, currently a lot of this data remains untouched, simply because people do not see the value of it.

In rank 4 and 5 come a few challenges that are either really specific (e.g. asynchronous working of data architectures and excel being outdated) or rather vague (e.g. hard to determine the future). Both categories are useful to consider throughout the implementation model development, since they indicate special cases in which implementation might fail, but are not acknowledged as being crucial.

Rank	Key challenge	Freq.	Context
1	People management	6	Aging, user satisfaction, resistance, expectations
2	Maturity of Industry 4.0	4	No advanced data capacity and algorithms
3	Chaos of data already available	3	Unstructured, old data
3	No standard option that fits all factories	3	
4	Determining the future	2	We cannot predict the outcomes
4	Asynchronous working of architectures	2	Amazon to Azure, etc.
4	Radical change of business processes	2	
5	Sharing data beyond borders	1	Related to end-to-end integration
5	Excel is outdated for large data entries	1	Yet the most used tool
5	Determine the right business needs	1	How to know what to improve?
5	Consistency in reporting	1	When employing Industry 4.0 in organizations

Table 2.5: A list of key challenges perceived at digital transformation in a supply & planning environment.

2.5. GAP analysis

In the introduction, chapter 1, it was briefly mentioned how current adoption of the novel technologies related to Industry 4.0 is remaining utterly quiet, while research and innovation is introduced at an increasing pace. Consequently, the introduction proposes a solution to overcome this deviation by making use of an implementation framework. Providing companies with a step-by-step model, reduces the risks associated with the adaption barriers, while also increasing the rate of adoption through the formation of solid and clear basis.

This chapter elaborated upon existing research in the field of available technologies, improvement methods (i.e. lean and agile), implementation methods (i.e. continuous quality improvement and DMAIC), and ways of assessing critical parameters and variables (i.e. SCOR and BSC). Moreover, a practical view was added in which multiple case studies, adoption barriers, and practitioners' perspectives were assessed. Through the conduction of a qualitative research, in terms of interviews, the last needed information was obtained to develop an effective digital transformation implementation model for the supply & planning of complex manufacturing companies.

Through comparison between the practical and theoretical background, multiple GAPS were identified. GAPS were identified as such, when a practical problem or challenge had no sustaining background or information in the related literature. For example, the interviewees mentioned the development of an overview showing the capacity and infrastructure. Many different approaches to this action can be taken, but the literature about Industry 4.0 implementation is not explicit in doing so. However, through a sophisticated literature review, solutions were raised to these GAPS, making them obsolete when incorporated correctly through the implementation framework. The found GAPS are the following:

- **Unambiguous representative overview:** *multiple causes point out that the use of an overview is necessary to describe the existing technology and to understand how future technologies fit in the operations processes associated with supply & planning;*
- **A methodology to address the most important aspects first:** *effective implementation is critical within Industry 4.0 to foster further development and innovation. A significant portion of the implementations done so far are based on existing and known inefficiencies, which might not be the best suit for digital transformation;*
- **A clear set of subsequent actions for actual digital transformation:** *case studies show that the technologies related to Industry 4.0 are ready for implementation, however various adoption barriers are yet preventing companies from making utilizing them;*
- **A framework in which these actions are structured:** *different models were identified in subsection 2.3.2, however, none of them offered a descriptive implementation plan that ensures full coverage;*
- **An evident overview of existing technologies and their applicability:** *through the extensive list of digital transformation-related technologies it becomes difficult for layman to understand the wide spectrum of technical solutions and their opportunities.*

2.6. Summary

This chapter elaborated upon the different aspects relevant to create the artefact (i.e. implementation framework). Up to this point 'Problem identification' and 'Objective definition' of the research methodology (Figure 1.1) have been addressed. These two stages mainly focused on the research relevance and were to answer the first three sub-questions. chapter 2 provided an answer to these sub-questions and already hinted upon the relevant attributes to sub-question 4. Other than answering the first sub-questions, this chapter also clarified on the supply & planning and industry 4.0 domain introduced in chapter 1.

The first sub-question *"What steps exist in an implementation process and framework?"* was approached from multiple angles. The lack of available use-cases that actually describe the full walk-through of their implementation process rose the need for alternative options. One particularly well-established improvement process utilized within the industry is the use of Six Sigma's DMAIC. Using this model as a foundation helps practitioners to easily comprehend the essence of each stage - while looking for opportunities rather than problems. Moreover, inside each of these stages there is a multitude of actual actions that need to be executed. With help of the interviews with practitioners and the model by Aitken *et al.* (2004) these detailed stages were identified.

Key characteristics, as defined by sub-question two: *"How are the key characteristics of a supply & planning environment that are required to construct an Industry 4.0-architecture found?"*, infers the exploration of the supply & planning environment and its interdependencies. Figure 2.3 clearly shows how the different planning processes relate to the entire production operations process. Knowing that improvements mainly arise from identifying the lagging processes and focusing on them, we identified two methods that are particularly effective in identifying these lagging processes by finding the lagging (i.e. key) parameters. The BSC approach was especially effective in this, while the SCOR approach enabled a lot of useful insights in the parameters to consider, including their possible KPI's.

To understand the basics of the factory of the future; or Industry 4.0 in particular, we have answered sub-question three: *"What are the available Industry 4.0 technologies that aid supply & planning departments?"*. For this sub-question our focus shifted initially to supply chains, since supply & planning are the key chain between (external) supply chains and the (internal) operations. By doing so, thirteen enabling technologies were identified. The variety of these technologies clearly indicate the significant opportunity associated with the Industry 4.0-concept. Hence the need for an implementation framework.

Finally, throughout the literature review small parts of sub-question 4 (*"What must be incorporated to develop a sustaining process that fits into the company's culture?"*) were already found. Challenges denoted in Table 2.5 and Figure 2.8 clearly show what barriers need to be addressed in an implementation framework to enhance its full potential.

3

Framework design

In the year 2020 companies can find often more similarities in their way of operation than exceptions. At the very basics, a company buys its resources: may it be human capital; raw materials or physical objects, then converts this into a product or service, and finally sells it in order to exist. This general view on a company's business process allows to distinguish between the different tasks undertaken in order to reach the overarching goal, e.g. buy, create and sell, regardless of the company of consideration. Such strategy is applied to frameworks where a particular process is separated into recognizable steps that are the same for each company within the scope. However, the strength of such framework is where the contradictions in the way of operation are addressed and shaped.

The framework strategy of this work focuses on this simplification of business processes and realigns them to generate a perfect fit to the existing technologies and future innovations. A generic batch manufacturing supply & planning process is illustrated in subsection 2.1.1. This business process is applied differently to each factory, e.g. use of particular (ERP) software or the way of planning (First in First Out (FIFO), etc.), are just few of the many variations based on the available resources within a company. It is this diversity that leads to a first challenge in the area of development; there is no 'one-size-fits-all'-solution. The framework should offer companies a strategy to reap the benefits of technological innovation and to enhance their existing operations, by means of simplification.

By careful assessment of the literature and having meaningful discussions with experts in the field, a design was made. At first, a company should have its input ready before any simplification can be made. Subjects like data storage, way of working (WOW) and reasoning should be known in advance. After these requirements are met, processing of the actual framework can take place. Through this framework a set of existing challenges are avoided and key stages are carefully executed. Finally, a set of actions were undertaken that have made the factory considerably more effective. However, there will always be room for improvement, thus a final highlight of key actions at the end of this chapter is made.

This chapter will elaborate on the consecutive stages of the model, including a detailed explanation of the required steps taken at each stage. Figure 3.1 with Figure 3.2 show the constructed model according to the information obtained in chapter 2. At the very basis of this model lies the DMAIC (i.e. define, measure, analyze, improve and control) approach from subsection 2.2.3. As indicated in said subsection, the DMAIC model suits well to the difficult and holistic nature of Industry 4.0-implementation. Therefore providing a perfect backbone and overlay for the actions to be taken.

Inside the backbone of Six sigma DMAIC lies another supporting frame in the form of the Continuous Quality Improvement plan of subsection 2.3.2. This model was found to perfectly describe the required intentions to assess which process must be improved, including an actual improving approach. Moreover, the results from the interviews shown in Figure 2.16 display a fair amount of similarities with quality improvement model, making it relatively simple to combine the best of both worlds. As a result, the different digital transformation implementation stages were conducted. One major difference between the implementation model and the quality improvement model is the distinct checking stage of the quality model, which is integrated into the separate steps of the implementation model.

Since understanding the nature of Industry 4.0 and its related technologies is rather difficult. Extra clarifications were added in line with the topology provided by the RAMI layers of subsection 2.3.3. These green overlays hint upon the focus of the corresponding stage with regards to the RAMI model. As one can clearly see, all functional layers of the RAMI model are addressed throughout the implementation model, allowing the full use of novel technologies and innovation from subsection 2.2.1. The main connection between these overlays and the individual actions is the focus gained from the stage 'business overview'. In this stage, RAMI is linked to the variety of opportunities allowing one to focus at the right solutions and tools according to the business overview. To even further delineate between the type of actions, two categories were made: focus on physical and focus on digital aspects. Hinting the user upon the approach to be taken.

The model as shown in Figure 3.1 is designed such that it can be used by any organization involving complex manufacturing sites, regardless of the Industry 4.0-related maturity. Iteration, i.e. the feedback loop between 'evaluate' and 'analyze', allows businesses to reuse the model over and over again. In subsequent loops the focus is likely to shift due to a shift in operations opportunities associated with the increased technology usage. Moreover, the use of more novel and sophisticated technologies will evolve over separate loops as well. For example a company might just introduce simple sensors at the start, but will go over refined algorithms, autonomous manufacturing and end-to-end integration in the loops to come. Especially this loop will aid the increasing adoption rates as the managers become more effective and efficient in going through the whole process. Furthermore, particular stages like digital reporting and OT & IT merger might drop out at some point, due to the increased novelty.

3.1. Define

3.1.1. Objective identification

In early stages of the improvement implementation plan, a company should consider its full strategy (Crnjac *et al.*, 2017). Strategic planning is often performed in a professional centralized team, usually consisting of established managers, senior consultants and experts. These teams develop a roadmap that is deployed among the whole organisation. The focus of these centralized teams is to establish a generic strategy that fits to the organisation as a whole, thus standardizing the way of operations. Such strategy can involve multiple aspects ranging from collaborative business processes to specific technology use-cases. After the mission has been refined, the task of these teams comprises resource allocation of both physical and virtual objects as well as tacit knowledge and support.

Throughout the organizational road map multiple locations will adopt the new improvements which leads to specific adjustment to fit local needs. The broader mission is still adhered to, by simply shaping these organizational demands to local business and/or manufacturing processes. This stage is crucial to allow innovation happen company-wide. Without tailoring, the structural changes are not likely to be adopted nor will they achieve their full potential. For this reason it is important to pay extra attention during the 'define'-stage as this work focuses on plant-level implementation.

Through mergers, strategic advances and difference in maturity, plants within one company can differ a lot from one another. Even manufacturing processes can have a completely different set-up due to the difference in available resources at a particular moment in time, despite being the same in nature. Such difference also alters the way of implementation for each factory. Imagine factory A to use VGA connections for visual information transfer while factory B uses HDMI as visual information transfer. An one-size-fits-all approach will not work here, unless some modifications in the strategy have been applied. This strategy consists of a variety of options; all visual connections are replaced by the newest version (HDMI), allowing future projects to be adopted more readily as well; a second one can be found in the use of adapters, there are plenty of HDMI to VGA transfer possibilities; and many others. However, each option has its implications.

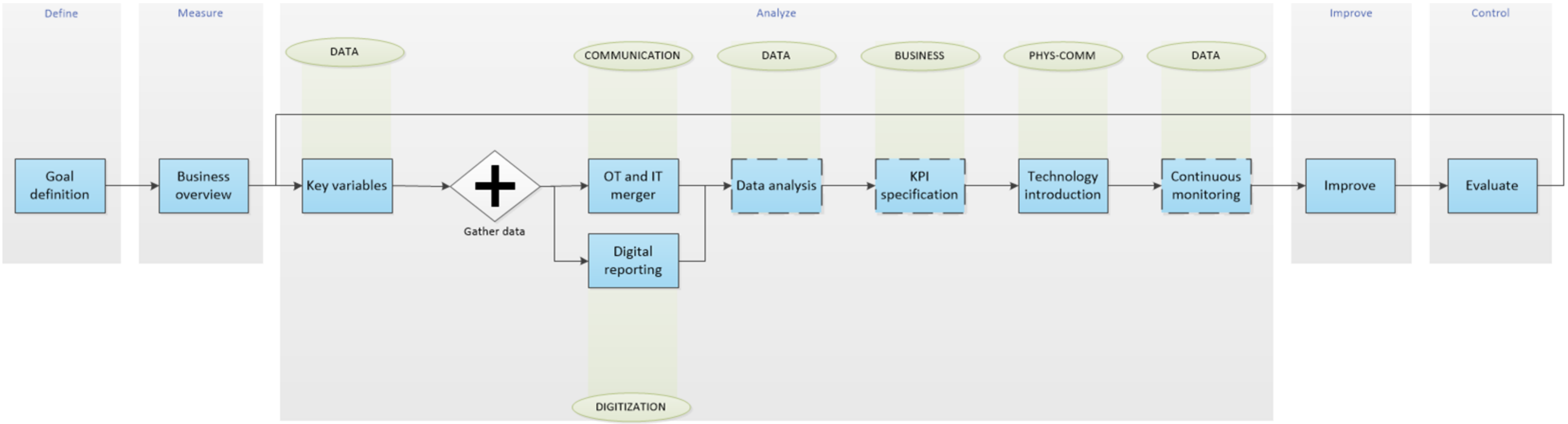

Figure 3.1: The digital transformation implementation model for supply & planning environments of complex factories.

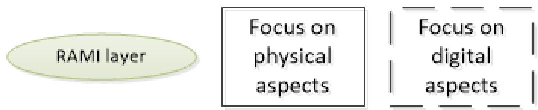

Figure 3.2: A legend explaining the 3 different types of function blocks of the implementation model.

Industry 4.0 capabilities often show similar challenges as aforementioned example. Connectivity between separate modules, either being physical objects or software, is key in the operability of the Industry 4.0-era. Moreover, the way how the business process is designed determines the applicability of a particular technology. This demands local teams to know the very basics of the system in place. Information like this can be utilized through the actual implementation stages, where the organization-wide philosophy is intertwined with the plant specific operations.

Key aspects in this philosophy are the deeply rooted goals of the general organizational strategy. Efficiency improvements, continuous monitoring or the bigger picture (competitive advantage) are just a few of the many different explicit targets a company could have. However, all of these imply truly different implementation plans for each factory. In the case of continuous monitoring one factory could measure each of its variables inexpensively, while the other has to invest significantly to measure only one variable. In the latter, it will be important to identify the major variables that contribute to the performance, since continuous measurement of these would be sufficient.

To identify the right needs, a stage within the implementation process is dedicated to the development of an overview in which all these aspects merge and solidify the implementation strategy. However, before one could start this process, it must be known what exact objectives must be reached. For this, a clear implementation vision has to be extracted. According to the literature, multiple reasons for improvement plans introducing smart technologies, exist. A list formed by Liere-Netheler *et al.* (2018) provides insight in the general drivers for companies to adopt digital improvement plans:

1. Process improvement;
2. Workplace improvement (safety, ergonomics or usefulness);
3. Vertical integration;
4. Management support;
5. Horizontal integration (information share along the business process);
6. Cost reduction;
7. Customer demands;
8. Integrated supply chain;
9. Innovation push;
10. Market pressure;
11. Laws/Government;
12. Employee support.

Each of these objectives differ the strategy throughout the implementation process as they require a different focus. For example, when the improvement evolves from a technology push through the company, the development of technology plays a central role. In the case that 'customer demand' is the fundamental reason, the focus switches to customer needs and, often, flexibility to which the implementation must adhere to. In all four layers identified by Chaopaisarn and Woschank (2019) (i.e. physical, data, cloud & Intelligence and control layers) various solutions can arise depending on the characteristics of a goal. Fully using the potential of business intelligence is more likely to fit the demands in a customer demand driven objective, while adopting key technologies like RFID and/or bluetooth are prone to innovation pushes.

For these reasons, identification of critical goals and objectives is the first step to undertake. Alignment between the organizational objective and local demands is principal for successful implementation (Liere-Netheler *et al.*, 2018). Using the established foundation, more attention can be paid to the building blocks on top of this foundation. The consecutive stages of this implementation framework rely on its foundation, as this defines the urgency of the project. When future decisions are taking too much time, one should consider to go back to this stage and rethink its purpose. Identifying goals is an iterative process because business needs can shift along the way.

Shortly after concluding the current digital transformation goals for the specific plant, a more careful look into the business process is done. It is these processes that allow companies to go from market demands, to manufacturing, and finally to the ultimate objective; making money. Many of these processes evolved over time and have been shaped due to external influences such as customer needs and competition. Since these changes emerge around one market need, they are often inefficient to others, encompassing an inarticulate system. To negate the effects of small process adjustments over time, several improvement studies have developed. Lean and Agile have been adopted widespread in the industry to streamline internal business processes. As a result, processes have become more efficient in achieving the multiple objectives for which they were designed, e.g. invoice processing, manufacturing or forecasting.

In digital transformation, these established processes provide the basis for development. With use of the business flow, one could easily deduct the many sub-processes underlying the main task. Each sub-process requires its own actions, such as sending an email, storing data in a file or interpreting results. It is these sub-processes that are rusted in our way of working, since they have been done like this for a long time. The focus of lean is to eliminate the sub-processes that contribute to a particular type of waste (Mrugalska and Wyrwicka, 2017). However, the remaining actions are oftentimes kept untouched, while specifically these activities rely on renewal. Digital transformation is one answer to this renewal.

3.2. Measure

3.2.1. RAMI overview

In order to pinpoint the exact sub-processes that could improve by means of innovation, a model is applied. This model originates from 2015 and is focused on the grouping of highly diverse aspects in a general model. Multiple layers in a factory are affected by the digital transformation. All these layers are addressed separately as they imply different effects on the process as a whole. Layers stretch firstly between physical assets (e.g. sensors) and the business sub-process (e.g. performing an action), secondly they vary between the different sub-processes (e.g. from development to operations) and finally it alters hierarchy within Information Technology (from product level to the connected world) (Schweichhart, 2019). Figure 2.15 shows the involved aspects of this reference architecture by visualizing the three dimensions of integration. From this RAMI model, a two-dimensional structure can be extracted. This structure, slightly adjusted to the implementation frameworks' needs, combines both the business layers and business processes (former lifecycle) in order to create a comprehensive overview of the current operations. Application of this model deduces the complexity of the problem by dividing it into multiple small building blocks that are addressed separately throughout the implementation framework. Such approach allows straightforward and effective elimination of sub-processes that are either old-fashioned or just inefficient. Also, it ensures full coverage of the relevant business processes, as the boundaries may fluctuate a lot. Moreover, this approach allows for various objectives to be realized within one simple model. For example, developing autonomous production will go smooth when each human decision is identified and portrayed against the necessary data. Similarly, cost reduction becomes much more apparent when time consuming tasks, involving manual handling (e.g. writing an email), are diagnosed.

This thesis is focused on the supply of raw materials and the production planning within factories. This clear distinction between other side-activities such as transportation, maintenance, and financing, requires a clear-cut use of the modified two-dimensional RAMI model which enables a streamlined view on the business process from start to end. Figure 3.3 illustrates the distinct layers and processes that are of interest within the scope of the implementation model. As indicated in subsection 2.1.1, the main processes evolving around daily manufacturing are forecasting, procurement (strategic and operational), order processing, production planning, storage and production. This major process is similar in nature, but different in execution for each manufacturer. For the factory of interest, it is important to describe each individual action, underlying the business process, and dismantle it to the layers of interest (functions, data, communication, digitalization and physical things). To simplify the analysis of all separate actions, one could make use of former Business Process Management Notations (BPMN's) or ISO 9001 reports, for instance. After all individual actions are defined, more attention is paid to the underlying functions. At each action, incentives for the action are important to monitor. The complexity of these functions can range from "if condition A exists, action B is performed" up to 30 different preconditions with multiple outcomes. At first, it is sufficient to only mention the question to be answered. For example, during procurement, functions of interest are "which supplier is cheap and

Figure 3.3: The modified two-dimensional RAMI model specifically fitted to the digital transformation implementation plan.

can fulfil our specifications?", "what are our minimal requirements?" and "How much of raw material X do we need?". The answer to these functions allow the overarching action to be undertaken. Both the input and output of the outcomes of these functions are sources of data.

The data layer describes what kind of data is required for the execution of the function. Data from various sources, e.g. databases, excel files, or reports is retrieved and fed into the functions. Identification of the data provides a significant layer of lists with parameters that vary over time. Examples are quality data (i.e. to decide if a batch can be sold), warehouse stocks with capacity (i.e. to buy raw materials) and maintenance planning (i.e. for production planning). After registering the data required, the focus shifts to the location of this data. How and where is this data stored and how is it retrieved. In other words: communication

Communication describes the type of flow between data providers (e.g. sensors) and the lists of data. Various lists of data are required within the business processes and therefore, require multiple variations of communication. Especially the non-registered communication like customer or supplier emailing supply a significant amount of unstructured data, but is essential for the business process to run. Other communication sources comprise internal servers and documentation or cloud applications. A useful note, often used in business process management, is the registration of the type of communication. Both pull and push describe how the communication takes place, either by requesting the data (pull) or by "automatically" receiving the data (push), which obviously depends on the person of interest.

Everything up to communication is known by now. Now it is key to describe the layer between digital communication and physical objects. How is data transformed from a physical state (i.e. being tangible) to a virtual state. Furthermore, the underlying application is of interest as well. Observations can be written on paper and then be copied to a PDF-file or registered in an Excel file, which will influence the way of communication in the layer above. Another option can be found in incoming orders from customers. As their demand is unclear to the supplier, we consider the digitalization to occur via email.

Or by other words: they know their demand and they write it down on an email (order) and send it to the salesman. The salesman will, on his turn, put this order into a database like Excel. Spotting these (manual) connections favor automated digital connection-solutions in future progression of the implementation plan.

Finally, the physical assets providing the data are collected in the RAMI model. The focus of this layer is to portray all physical elements that generate the data mentioned in the data layer. So market demands evolve from physical usage at the market side, which can be found in warehouse/storage stocks of a particular product. Data about production capacity emerge from the availability of machinery inside the manufacturing process, thus requires machinery as physical asset.

Throughout the creation of this RAMI model, it becomes apparent that some of the data required to perform the functions, is not flowing in via communication nor digitization. Data about production capacities is often just a number (i.e. average capacity) that the practitioner knows by heart. Therefore, he/she does not need to retrieve the number over and over again. Simultaneously, one could observe what data can be considered static, which can either be made dynamic to enhance the effectiveness, or remain static in the new digitized workflow.

The use of this RAMI model in contrast to other 'business process'-measuring methods follows from its useful connection between business processes and Industry 4.0. Moreover, it is particularly useful to pinpoint the interdependencies of critical Industry 4.0 layers (e.g. communication) which no other model delineates on such level of detail making it truly superior to other useful models.

3.3. Analyze

3.3.1. Key variables

Now it is clear what business processes are executed and what information and processing is required to do so. The next stage is to decide which key variables are present in the data identified in the data layer. Digital transformation involve numerous solutions to numerous challenges faced by companies. To avoid lack of focus and inefficient progression, special attention is paid to the critical data. It is this data that can significantly affect efficiency when either badly incorporated in the new digital model or improve the process when applied correctly.

A key feature of a process variable is the fluctuating nature. According to Aitken *et al.* (2004) a variable is described as "some characteristic that differs from subject to subject or from time to time". To discriminate between typical and key variables, one must determine its influence on critical function characteristics (Aitken *et al.*, 2004). For example, while deciding which suppliers to contract during strategic procurement, multiple data sources are consulted. Data about minimum raw material specifications, required volumes, travel distance, and production prices could all be incorporated into the decision-making process. If a company is located in a traffic central location (e.g. easily accessible harbour), the decision is less dependent on travel distance or delivery time (i.e. these will all be similar), but still depend significantly on a certain grade of raw material.

Identification of these key variables allows delineation between important and irrelevant digital adoption. Structural definition of the important variables allows scoping throughout the implementation phase. Improvement of the business process is accomplished by leveling out the factors that have significant effect on the outcomes and fluctuate a lot and leaving the ones with minor effect. When a company succeeds in defining these key variables and is able to make them somewhat constant or monitor them more accurately, they are able to respond quicker and more efficient in decision-making processes. At a later stage, it is even possible to utilize this data in algorithms to make the decision-making process autonomous.

The reason for key variable capture is quite obvious and so is the strategy to identify them. Besides experience, multiple tools and analyses are useful to define these key variables. In the first stage one should come up with the datasets that are known to be prone to fluctuations. A variable like delivery time by boat can greatly depend on weather if the distance between supplier and customer is more than a few days, giving a fluctuation of several days. If this raw material is planned exactly on the day after planned arrival, valuable production time is lost when delay occurs. This particular type of information, and the likelihood of it taking place is a matter of experience. When this event occurs more often than wanted, we will consider it to be a key variable.

Other tools, such as a Pareto diagrams, cause and effect diagrams, quality teams (Aitken *et al.*, 2004) and Design of Experiments are all effective in a different manner. This study does not focus on the particular description of when to use and how to use these tools, there are simply way better explanations around that will do just that. However, a short introduction of each of these is given below:

- **Pareto diagrams:** A Pareto diagram is designed to organize all errors into one diagram by descending order of occurrence. With the data available, this diagram is filled and allows to divide the "important" errors from the "irrelevant" errors. By means of a cumulative expression, the "important" errors can be found in the first 80%. The variables behind these errors are then specified to be key variables;
- **Cause and effect diagrams:** Also known as fishbone or Ishikawa diagram and aims to identify the underlying sources accountable for fluctuations, such as quality;
- **Quality teams:** A quality team can jointly determine the key variables by simply interviewing the process owners of the business processes in consideration. Special attention can be paid to sub-processes that provide extra value to the business;
- **Design of experiments:** A rather technical tool is the use of Design of Experiments (DoE). DoE originates from laboratories where particular variables are kept constant, while others were deliberately changed in order to see the effect on the outcome. Such tool can be useful for environments where the parameters can be kept constant and allow for more precise determination of key variables.

It could be the case that not all key variables were identified through the process, because they were not known, did not present themselves in the tests or were just not considered to be relevant. This will not lead to any issues in further progression of the implementation model, as they will reveal their importance once the model is conducted once. In a future stage concerning determining goals and setting KPI's, these left-over can be involved in a next sequence.

3.3.2. Digital reporting

Using the input as described in subsection 3.3.1 opens up the path to make the first minor improvements. Some of these improvements have already been implemented by some companies when employing lean and/or agile manufacturing. Also in light of corporate responsibility, like people, planet, profit, organizations have diminished the paper usage. That being said, this stage comprises often less efforts than others. However, the main concern for this stage is the reason for digital reporting and the way of storing, which can be different for other improvement tools like agile and lean. Thus requiring a second examination on existing digital reporting.

During the manufacturing process, the workforce close to the installation (operators), can observe the system carefully. Specific changes during operations are clear indicators for failure or inconvenient fluctuations at a later stage, as was indicated during the key variables stage. Observation of these changes is often written on a production paper held by the operators. At the end of the shift, these pieces of paper are collected and stored elsewhere. With the development of Information Technology (IT), different ways of filing these observations have evolved, for example in Excel templates. However, the same rules apply to these versions of storage, they are saved at the end of the shift and are not accessible elsewhere in real-time. Observations that involve big impacts are communicated via person-to-person contact and have a delay depending on the amount of people involved.

In case such observation has a small impact on subsequent processes within the company, it is not likely to reach the salesman until the end of the shift. However, this small impact inside the company can snowball outside the company with, for instance, missing its transport overseas. By the time the shift is over, the salesman will find out about this small delay and is not able to inform his customers in time, resulting in a loss in sales. If it were possible for the salesman to find out about these observations in real-time, he would have been able to contact his customers and come up with a plan of action.

Former example illustrates the need for real-time observation (i.e. data) coverage. This is a key concept to understand while digitizing reporting of separate organizational bodies. Tools like Office 365, Google Drive or Dropbox enable companies to share different types of files across multiple business units, in which changes and adjustments can be seen real-time by all parties. If something concerning appears to one of the involved teams, they can simply communicate the details and adjust their process to fit the new developed situation.

To specify where digital reporting is required, one should use both the used RAMI model of stage 2 and the characterized key variables of stage 3. The first step to undertake is to digitize the recording of all key variables that are just written on paper as indicated in the RAMI model under "digitization". The first objective in this stage is to create a digital record of events to enable future data analysis. Situations like malfunctioning equipment, lack of resources or quality issues can be relevant according to the key variables and are relevant to understand the existing bottlenecks and their origin.

3.3.3. OT with IT

Provided with the new digital data entries at several stages of the business process already caters initial data analyses. However, there is another set of data that is readily accessible for many manufacturers: Operational Technology (OT). The third industrial revolution involved Programmable Logic Controllers (PLC) that use incoming process data to make preprogrammed decisions in other parts of the process. An example of this data is the temperature inside a reactor vessel which may trigger (via PLC) the opening of a valve when exceeding a predefined limit. The response time of these sensors, PLC's and actuators is generally fast in the span of milliseconds. Because this data is generated fast and often (a few million entries within an hour), data logging and storing over a long period of time is often not feasible. Therefore, this stage within the implementation process only focuses on obtaining a dataset that is representative for the average operations. By capturing different variations, employment of data analysis allows specification of the causes for these fluctuations.

It is considerably difficult to determine the background, usefulness and type of data when being used for PLC programming. At the same time, it can cost significant efforts and money to retrieve and store the data obtained from PLC's. Moreover, the bandwidth and processing power of and to PLC's face issues when large amounts of data are forwarded to a secondary database. Here it is important to just gather data relevant as key variable during stage 3 of the implementation framework. This selection will reduce the drain of processing power on the PLC side, while making the data collection efficient as well. In subsequent stages, after the first loop of the implementation model, deeper insights allow useful extraction of other PLC-fed data.

Different approaches to collection of data can be taken. All depend on the maturity and arrangement of the controller systems. Minor differences between vendors, DCS (Distributed Control System) or PLC systems and the architecture of a Supervisory Control and Data Acquisition (SCADA) can favor or oppose the data storage or logging onto an IT device. Mostly this is just a plug and play-principle where one connection by cable, ethernet for instance, is sufficient. Moreover, it is important to note that real-time data capture is not within the scope as of yet. Special care must be taken to avoid data leaks or latency on the existing and running process, since PLC's are often employed to ensure safety of the manufacturing unit.

By simply connecting with the existing manufacturing system (DCS/PLC) or via a PROFIBUS/PROFINET connection, one could allocate a part of the data on to a digital time-series database like mySQL. In the Industry 4.0-philosophy there are multiple ways to do this efficiently, like only logging changes, rather than the actual output thereby reducing the load on the database. In case of this implementation stage, this is not necessary. By capturing the data output for a certain amount of time (weeks-few months) one would have enough data to understand the recurring inconsistencies while not leeching too much of the processing power required for operating the factory.

3.3.4. Data analysis

After five stages of careful mapping a significant load of information is established. This information range from simplifications, e.g. RAMI model, to actual data capture by digitizing and a connection between OT and IT. Having this data is still far from full implementation of Industry 4.0 related principles. In order to get to the state-of-the-art technology, assessments are mandatory. The first few elements of concern, the key variables, enable insights in the general performance of the process. Thus, the data collected amplifies inconsistencies and unwanted errors.

To understand what causes the inconsistencies requires data analysis on the data set. Event-based, time-series data shows situations happening and enables comparison between different data sets of separate key variables. For example, the arrival of raw materials by truck, is compared to the Warehouse Management System (WMS) that tracks actual stocks of raw materials. By doing so, the manager discovers that there is 2.5 day delay every weekend. After further research, he finds out that the WMS operators leave early on Friday and leave the remainders for Monday. As a result, the buy-in of raw materials on Monday is incorrect, because the stocks are not correct. In the case of high throughput materials, like bulk products, this will have a minor effect. However, when the discrepancy concerns the sporadic usage of a material that have a large Minimum Order Quantity (MOQ). A part of the storage capacity will then be occupied by a materials that is just slowly consumed, eliminating valuable storage space.

Data analysis exposes inconsistencies as described in previous example and aid for effective implementation of innovation. In order to analyse the available data in an efficient manner, an appropriate understanding of data is required. The concept of the 6 V's was introduced to establish a solid support for Bigdata usage. Since Bigdata is data, but flexible, (often) real-time and highly scalable, the underlying principles of Bigdata allow for clear utilization of traditional data as well. The underlying 6 V's of Bigdata involve Volume, Variety, Velocity, Value, Veracity, and Variability.

Data sets can extend to long lists, depending on the interval of data logging, as well as the various dimensions of measurement, e.g. the amount of sensors. These factors contribute significantly to the volume of the data set, thus requiring a different analysis approach. Statistics for large volume datasets are generally superior to the sets with only small volumes, due to the large sample size (n for statistics). However, the larger the data set, the more computational power is required.

The volume of data also relates to the variety of data. When more data sources are combined into a dataset, the variety increases. Each row of data represents a different parameter and has a different meaning, e.g. temperature and pressure. While doing data analysis, this difference allows to find inter-dependencies between multiple factors which will make pinpointing causes of inconsistencies much more straightforward.

Velocity of data relates more to the real-time realm of Bigdata, that is the continuous flow of large volumes of data. Since at this stage, just 'old' data is being used, the velocity characteristic is less relevant and out of scope. However, acknowledgement of the velocity dimensions will make the data analysis to adapt to future purposes as well. For instance, when looking at a large set of stock volumes inside a warehouse, one will already imagine the possibilities when this data is collected real-time when looking for deviations in the data.

The fourth dimension, value, describes the value BigData can bring. For instance, you can have data about your order history containing information such as order size, location of customer, manufacturing and delivery time. And if used separately, they provide insights into the strategic information such as countries of interest and average shipping times. However, when combined altogether, one could create more value by linking average manufacturing times to particular customers, as well as their average order size, to predict future consumption as well. Knowing what value evolves from maximum utilization of the data makes it easier to define the origin of particular inconsistencies.

A fifth understanding of data lies within veracity. Perhaps, this is the single most critical dimension in meaningful analysis, yet hard to measure. By means of previous steps, data is now collected by a variety of sources. All these sources collect data in a different manner, e.g. human observation, milliseconds measuring (sensors) or daily administrative tasks in a Enterprise Resource Planning (ERP) tool. Combining this data allows substantial insights as was described by previous V's. However, to ensure that these insights are correct, one must know the origin and quality of data. For instance, if the manufacturing information is filled onto a paper and then, at a random time throughout the week, entered in the ERP system, we will know that time of entry into the ERP system will not suffice for comparison with other time-based datasets. Another burden could be the recording of the data by human observation. An operator may opt to solve the problem straight away when recognizing a manufacturing defect, rather than store this information digitally and then starting to repair the process. All these minor details contribute to the accuracy of the data and therefore to the accuracy of the analysis. Acknowledging these details during analysis prevents incorrect cause-effect deduction and will increase the efficiency of the analysis.

"Garbage in = garbage out."

Finally, there is a factor called variability. Data is eminently susceptible to variations, we want it to change over time, after all. However, the threat lurks behind the unintended variations, like sensors that switch places and thus measure the same bulk, but at a different location. In the case of temperature sensors, this difference can make the data change structurally when applied on a distillation column. At an uncontrolled atmospheric storage tank, the change of location of a sensor is less likely to interfere with the data variability. Moreover, these variations can also occur due to non-human interactions, like outside temperatures. Structural effects like these will affect the outcomes of an analysis and must be known beforehand.

Now the underlying basics of data are known, a first step is to combine all information. Various data sources were identified during the RAMI process, such as ERP systems, order data and quality checks. On top of that, new ways of digital reporting and data sets concerning Operational Technology (OT) were added. All these different data sources require different software to access or have different formats. Generally, data is shown in rows (different variables) and columns (time/event-based entry) which supports exportation to csv or excel-like files. On their turn, these files can be imported to Excel, SPSS and countless other programs that can run a variety of statistics. When all historic data is identified and converted to one general type of file, the analysis can start.

Data analysis can be performed on many different levels, ranging from simple average calculations to full data mining. Regardless of the approach, a few factors play a key role during analysis. At first, it is important to spot the inconsistencies. When is the data entry much different compared to the general set. For instance, quality data is found to be important through the RAMI-process. Usually, the quality is between 99 and 101%, but at two instances it was 95 and 105%. These two cases clearly stand out and are noticeably interrupting an efficient flow, as the corresponding batches might require re-production or are sold at a lower price. Knowing when this data was generated, gives a time span (depending on the data about manufacturing time) to investigate what other deviations occurred, like a change in raw material composition. This investigation leads to discovery of crucial variables which can be monitored and controlled continuously when applying digital transformation.

The second critical step is to define the inter-dependencies. For instance, a company is likely to know that the delivery time of raw materials might affect the transportation date of its own products. Analyzing the data and looking for the dependencies provides values for the connections. *Raw material A* could delay the production process by a few hours, while *raw material B* could delay the process for a few days. Identification of these aid full-fledged customization in a later stage when applying separate technologies. It also helps to understand the full business process and the underlying principles.

A final step consists of establishing performance indicators. These indicators give in a hindsight the information a layman needs to understand the performance of the system. Data about raw material stocks together with production planning information give information about emergency purchases. If a raw material stock is nearly zero and increases quickly before a production, using that material, was planned, one could identify this as an emergency purchase. Add all these emergency purchases and put them against 'regular' purchases and you know the rate of emergency purchases. Said number comprises an indication of current performance and allows goal-setting during the next stage.

Although the data analysis stage involves multiple interesting characteristics and insights, there is no requirement on the amount of data and a minimum on the extensiveness of the analysis. However, to provide a clue on the necessary amount of information, a rule of thumb is to find at least 5 performance indicators that are operating below a preferred level. If there are too many, apply the Pareto-rule (Koch, 1999) where you aim for the biggest indicators that provide 80% of the inefficiencies. Since these indicators show 80% of your inconsistencies, they will provide the largest (and fastest) improvements when upgraded.

3.3.5. Setting KPI's

In the previous step, separate performance indicators were found. With the data obtained thus far, these performance indicators describe the past behavior of the business process. When applied over a longer period of time, e.g. months, one could monitor the average performance of the current system. Obviously, this performance determines the operational effectiveness (i.e. people, planet, profit) of the company. The goal of digital transformation will differ from company to company, but they share all one thing in common: improvement. This stage solely focuses on the improvements that can be made by setting specific goals, depending on the discovered inconsistencies. The goals consist of targets for the identified KPI's that are monitored and improved in the 'new situation'.

Through the interviews, several Key Performance Indicators (KPI's) were identified that are susceptible for improvement when applying a digital transformation strategy. This list of indicators can help one to identify which indicators provide valuable information and benefit the overall efficiency when monitored and improved. Bench-marking with other, similar, manufacturing plants helps to set the goals corresponding to the common KPI's as indicated in Table 2.4.

Through the implementation phases multiple objectives have already been addressed: process identification, process simplification and process harmonization. During the data analysis it became apparent what bottlenecks exist in the simplified processes. When eliminating these bottlenecks, the improvements should be noticeable by means of KPI's. For instance, the downtime is consistently at 20%. By data analysis it was found that 6% is caused by preventive maintenance and the remaining 14% is caused by corrective maintenance. However, 14% is rather high when compared to other factories, thus you want to reduce it at least by 50%. Since the origin of this high number is uncertain, after all, it could have multiple causes (e.g. faulty predictive maintenance, incorrect definition of corrective maintenance, incorrect use of the machinery), you want to uncover the data underlying this KPI. So now you found the KPI's, know how much you want to improve them and have an idea what is causing them to perform below preference.

3.3.6. Applying technologies

After setting goals, the actual implementation can start. In previous stages of the model, identification and simplification of the business process were key. These steps gave insights about what to incorporate and what to leave to a later stage for efficient digital transformation. The goal of this stage is to determine what technologies need to be used to suit the initial objectives of the organization as well as the improvement of essential cores of the business process. Since this step is part of the feedback loop, extra care is taken to digital transformation as a whole. When developing a solid basis for technologies to connect, future implementations can readily hook up onto the existing architecture.

As indicated in subsection 2.2.1, a large variety of technologies exist in the Industry 4.0-realm. Core to these technologies are data and connectivity. In order to have sufficient connectivity to transfer the generated and processed data, a data architecture is employed. Data architectures come in all sizes and forms, a Supervisory Control And Data Acquisition (SCADA) system consisting solely of PLC's or an automated Warehouse Management Systems (WMS) that measures current stocks are just a few of the many examples.

However, when applying the RAMI model to divide the business process in small pieces, the existing data architecture was exposed. This existing architecture comes with limitations as was identified during the data analysis, because some of the core elements were not measured real-time, hindering adequate interference. At this point, it matters how the process variable can be measured. Is it a static factor, like quality, then it can be measured at the same spot, using the same sensor or method. Is it a dynamic factor, like the warehouse stocks of a particular raw material, then you need a sensing system that is adapted to the shifting nature of the location of the raw material. For each of the separate key factors that were identified during the stage ”determine key variables” a way to measure (or digitize) it real-time is determined. For example, the machinery down-time is found to be a key variable. Within the PLC system it is already known whether a particular piece of machinery is running or not, thus a continuous connection between OT and IT is sufficient for real-time monitoring. A second example is the available stock levels of a particular raw material. One way to get real-time numbers is by applying RFID trackers on the packages. However, this requires extra handling stages such as placing the RFID tag and coding the tag (corresponding to the product) by the unloading operator. But at the same time, it offers high scalability in future stages when other parameters need RFID tags as well. Another option is the use of barcode scanning, which is less costly but decreases traceability. A third option is found in adoption of HMI (Human Machine Interfaces), such as a screen on which the operator can fill the data like amount of raw material added or removed. An easier solution compared to RFID tags, but also more susceptible to errors.

All these options arise from the portrayed technologies in subsection 2.2.1. These technologies are categorized per RAMI layer, to clarify their area of improvement as well as their application. Figure 3.4 visualizes the applicability of the separate technologies to each layer. Using this figure, one can identify which options are present to the challenge ahead. For instance, when having limited communication between devices, resulting in unnecessary human interaction, one could opt for Edge or Device to Device (D2D) related technologies. The edge approach connects the sensors and actuators to one central piece of equipment, that processes part of the data before sending it to the cloud. This allows for fast decision-making and shifting of the actuators, since there is no obstruction of data speed due to latency. The other option, a D2D approach allows for fast collection of all data which is then send to a central database. There is nearly no latency, so real-time monitoring enables adequate interventions. The clear difference in the two approaches is the connection, which can be wired for edge and wireless for D2D.

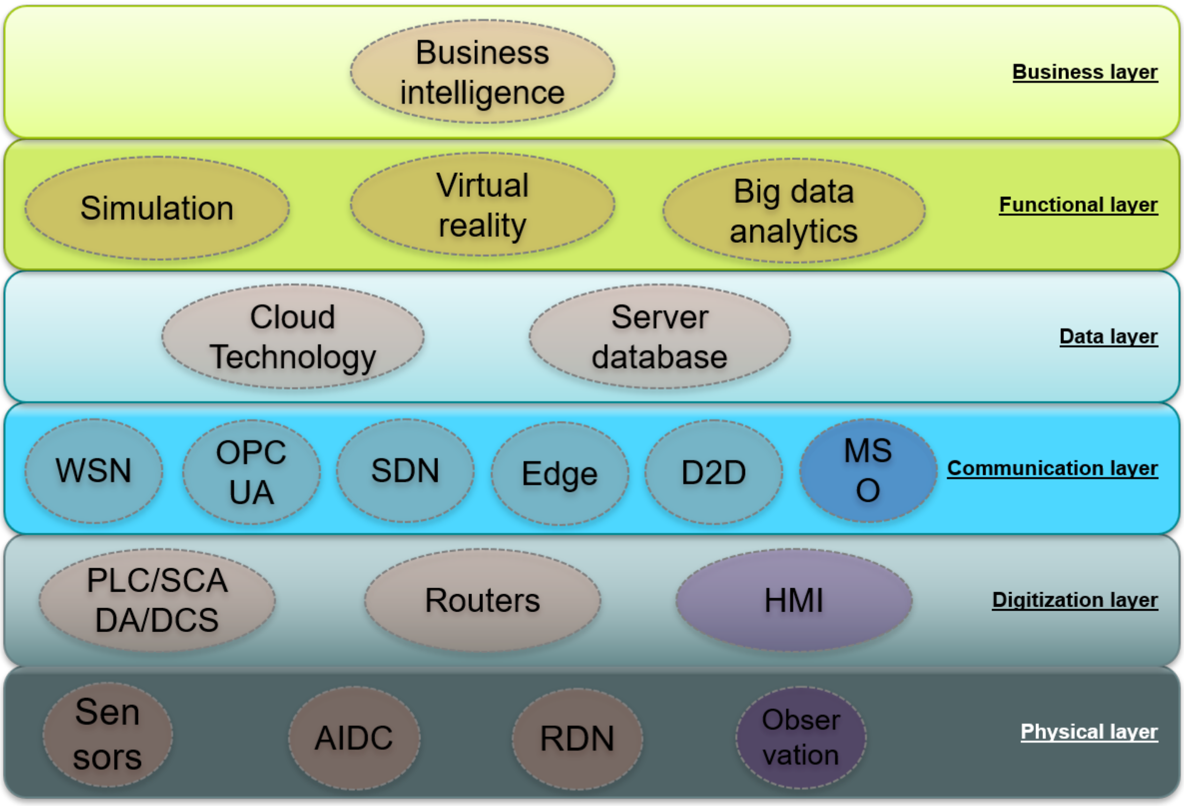

Figure 3.4: The smart factory technologies can be categorized among the separate RAMI layers. The showcased "red" technologies are found in smart factories and will aid digital transformation. The purple technologies can be intermediary technologies during the Industry 4.0 transformation.

When the implementation model was run multiple times, the focus from data acquisition could shift towards more autonomous operations. As a result, the functional layer becomes more extensive during the "applying technologies"-stage. To improve the functional layer, technologies like simulation, virtual reality and big data analytics are useful options, as indicated in Figure 3.4. Imagine the focus being production planning and the key variables identified is raw material availability. In previous implementation cycles, the data concerning this variable has been digitized and real-time information is made available by applying Internet of Things and cloud technology. To aid decision-making, depending on this variable, simulation could show the process owner what would happen with the raw material efficiency if the factory starts manufacturing product B rather than product A. Another technology, big data analytics, allow for strategic decision-making, because of the predictive behavior of the system. At full utilization, future raw material usage is predicted depending on all data collected and analyzed, enabling a just-in-time purchase methodology.

For every implementation cycle, different types of technology become a better fit to the facing challenge. Choosing between the available options arises upon decision-making tools, such as cost benefit analysis. By applying a monetary value to each of the aspects like usability, scalability and accuracy one could define the total cost and benefit of each of the selected options Cellini and Kee (2015). When these values are assigned, one could compare the costs and benefits and determine the most valuable option. Such approach is simplistic and gives insights into the added value of each of the options.

Another widely used tool is the Analytical Hierarchy Process (AHP) as a multicriteria decision mechanism. This tool has been used by various researchers to describe an uniform approach of selecting useful Internet of Things (IoT) platforms, devices, cloud services and databases (Contreras-Masse *et al.*, 2020; Durão *et al.*, 2018). The focus of this tool lies on the different criteria imperative to the operation of the actual device. Subjects like cost, security, training, support and device management are pre-determined criteria that are ascribed to each of the options either qualitatively or quantitatively.

After deciding which technology would suffice, it must be determined how this technology is applied. Sensors can be employed for countless applications, e.g. humidity, optical, image, motion, infrared, chemical, pressure and temperature measurements. Automatic Identification and Data Collection (AIDC) include items like RFID's, bar codes, and QR codes. Important in the selection process is to adhere to the objectives and scope of the technology itself (Khan *et al.*, 2017). For the case of observation as a physical layer approach, it must be determined what and how accurately something must be observed to aid the process. Similarly, when applying sensors or AIDC, an unit must be installed such that it accurately measures the data that is required further down the line at a functional layer.

Implementation of the selected technology should follow right after selection. Depending on the technology, a variety of prerequisites must be met to complete the implementation. Requirements like software packages, connection with existing servers/cloud systems and training systems need to be in place before actual adoption is possible. A widely used tool in the industry, to ensure correct implementation, is the Management of Change (MoC) procedure. By following trivial pre-determined steps, all necessary actions will be undertaken.

A new data architecture was created through this implementation stage. If performed correctly, the RAMI model has changed and must showcase the new business process. Therefore, the RAMI model developed earlier, needs to be adjusted in order to be recycled in the feedback loop of this implementation model. By redefining the RAMI model, it becomes apparent what new technologies need to be implemented for a fluent and efficient business process.

3.3.7. Continuous monitoring

With the technologies in place and the goals defined, one could start to use the data obtained. The real-time data flows through the set-up architecture and enables for process monitoring. Dashboards equipped with KPI's allow for performance monitoring in a hindsight. In the mean time, data about production is gathered that can be used for careful data analysis to find more inconsistencies that were not observable before.

The continuous flow of data clear the road to new business opportunities. For example, a factory diminishes the stock of a raw material by manufacturing of a certain product, called product X. Due to an error in one of the manufacturing units that is required for production of product Y, the production of upcoming products is advanced. As a result, the raw material of interest is fully consumed before new supply arrives. In previous situation, this stock data was based upon production numbers as well as delivery status, both processed once every 24 hours. Such latency causes a relatively late reaction on the purchasers' side which results in even more complications down the line. If the purchaser observes this discrepancy within time, there are plenty of options, such as delaying particular products within the production planning or accelerate the supply of raw materials.

Performance indicators are similar in usefulness, but require a different handling. Performance of the process is related to the structural actions performed. If the performance is below par, special attention to these actions is recommended. A following analysis could indicate the cause for this inconsistency and allows the company to take measures accordingly. Training, a shift in operations or technical adjustments are just a few of the many possibilities applicable in this scenario.

An example of a key performance indicator is the capacity utilization which indicates how well the process is running, depending on its limiting factors. If product Z could run at 15 tonnes/hour, the capacity utilization of product Z would be 67% when producing at a rate of 10 tonnes/hour. When observing this reduction in capacity utilization, several causes could be thought of; there could have been (un)planned downtime, a raw material that is out of spec and runs slower or there is insufficient storage space. Depending on the other data at hand, one could investigate the origin while it is happening, allowing to rule out more causes than when relying on "historic data". If a cause was found to consistently interfere with the continuity of the business process, additional actions like process improvements can be developed.

As indicated, this stage truly serves as an extension to the data analysis. Initial analysis allowed to find possible pain points within the business process. As a follow-up, this stage focuses on continuous monitoring to find these pain points on a real-time basis. In return, the faced dilemmas become (smoothly) solvable as they just occurred, while improvement proposals can attack the recurring challenges.

3.4. Improve

3.4.1. Improve

In the first stage of data analysis it was found what huge and common inconsistencies occurred during the manufacturing process. Through the second stage, continuous monitoring, a more refined and in-depth analysis was developed. This analysis include continuous discovery of causes for ineffective operations. With this information, lean manufacturing can take its turn. By elimination of waste, a more sophisticated and efficient process is developed.

Key to this improvement stage is the adaptability within the existing and future business process. By other words; it should not hamper future data integration. Common improvements such as on the job training, changing the order of actions in a standard operating procedure or adding/removing technical components to the manufacturing process are sufficient more often than not.

Since this stage is highly dependent on the faced challenge within a particular context (i.e. company), it is unfeasible to provide a particular list with options. Moreover, the steps undertaken up to this stage already provided the information required to find the issues, monitor, and analyze them. The actual improvement should follow from these initial actions and can be strengthened using rational ideas for elimination of sources of problems, and by using creativity via brainstorming sessions or adopting the TRIZ principle. In this TRIZ principle, a team is given 40 predetermined words that help to look at the problem in a different manner. Examples are asymmetry, e.g. by making the product asymmetric you can avoid unnecessary blockages, continuity, e.g. streamlining a batch process by eliminating all delaying processes, and turn around, e.g. turn around the order of operations to get a feel of irrelevant actions.

Together with logic and creativity, every inconsistency found can be eliminated. However, to remain productive and efficient, the Pareto (80/20) rule of subsection 3.3.1 also applies to this stage. At first, the focus was on the 80% of the important variables that affect the system. Now this 80 % applies to the inconsistencies that contribute the most to the reduction of performance (i.e. low KPI's). It is these issues that will improve the total efficiency a lot, when being solved with considerably low efforts.

A perfect examples of this stage, where the 40 TRIZ principles were applied is found in a solids factory. The factory faced difficulties with maintaining the quality of their products. By continuous monitoring of the quality together with the raw material intake, they found that one of their raw materials was not entering the system at a steady rate. When observing the silo with that raw material it became apparent that so-called dust bridges were hampering the flow. The previous tapered design of the silo's bottom was now changed to an asymmetric one, where one side was made completely vertical, while the other was diagonal. Asymmetry according to TRIZ helped finding a solution to the consistent appearance of dust bridges.

3.5. Control

3.5.1. Evaluation

Finally, after going through all implementation stages, a part of the business process was digitized, analyzed and improved. If performed correctly, this part of the process is future proof, as it is continuously collecting data and is connected to the bigger system, as well as fitted to the organizational picture adhering to the company's objectives and goals. In this stage, it is key to define whether the goals have been met and if the process indeed was improved. Moreover, the effectiveness of applied technologies is measured by taking a look at the performance improvements. At the end of this stage, the lessons learned enable smoother and effective when going back in the feedback loop. By performing this loop, new key variables are defined and improved, thus developing the business process to a new efficient standard.

By evaluation a list of recommendations for future implementation is generated. Recommendations such as how to perform analysis and how to select the key variables are key to successful reuse. These all follow from experience or via use cases such as other factories within a global organization. A valuable tool could be the comparison of performance compared to other similar factories within the organization, or in other words: a benchmark.

Another aspect of implementation effectiveness is user adoption. Digital transformation can imply autonomous processing, removing human interference. However, most of the times it is about introducing digital tools to aid human decision-making. Especially in these cases, human adoption is crucial to reap all benefits. User adoption is a factor which can be measured in itself, however, it does not support explain the reason behind user adoption, or the lack of. For that reason, user satisfaction is far more constructive in nature. By deploying an user satisfaction study, the team can find what should be done differently in future implementations.

Furthermore, people management was perceived as one of the most difficult aspects in digital transformation. Continuous feedback by means of surveys and interviews allow for evaluation of this strenuous condition. Motives for the adoption are different for each company and thus require a tailored implementation plan.

After the evaluation stage has been processed, the feedback loop starts. Every company has to improve continuously to keep its competitive advantage. Especially digital transformation takes time to happen. Multiple cycles of this implementation plan approve continuation in the bigger picture; moving from having an easy overview, to perform actions based of predictive analytics, and finally to have a completely autonomous business process.

3.6. Summary

This chapter illustrates the development of the artefact (i.e. the implementation model) and its functioning following from the literature study and interviews of chapter 2. Throughout the literature review it was already assessed what key steps must be undertaken for successful implementation (i.e. the answer to sub-question two). These separate actions have been adopted and merged into the implementation model in a logical and self-reinforcing manner. The very basis of the model follows a well-known and convenient method in the sense of the DMAIC. Developing a framework on top of this technique helps practitioners to easily grasp the essence of each stage.

The individual actions dedicated to each stage then explains what steps are undertaken for effective implementation. These actions are derived from a quality-improving model by Aitken *et al.* (2004) that already proved its effectiveness, as well as the input from multiple practitioners. The combination of both ensures that none of the essential steps are overlooked and simultaneously provides some sort of reference in terms of sub-actions to take (i.e. searching for key variables using either quality teams or the Pareto-tool). Finally, the individual steps were translated to the Industry 4.0-framework in the Supply & Planning environment using the knowledge obtained in section 2.1.

For each of the eleven action, within the five stages, it was indicated what specific actions must be set in motion. By explaining the final deliverable, e.g. a fully filled 2D-RAMI model or selecting up to 5 KPI's, it is depicted what the action should result to. Thereby maintaining the wide applicability of the model while providing a detailed guidance.

4
Demonstration

Previous chapter elaborated upon the implementation model crafted by information obtained via interviews with practitioners as well as existing literature dedicated to Industry 4.0, digital transformation and business operations. The implementation model aids practitioners, specifically in the area of complex manufacturing processes, to define the appropriate implementation strategy. Through a set of step-wise actions, a digital transformation is obtained, which is both practical - fits the local needs - and sufficient - provides helpful insights at any stage of a company's digital readiness.

Although this model was developed depending on many years of experience as well as information about state-of-the-art technologies, applicability and usefulness are still to be tested. By means of a case study, the applicability of this study can be perfectly tested. The case study of choice is performed in a company who's name is known at the research team, but kept secret for confidential reasons. The company is readily participating in digital transformation and follows the corresponding trends carefully. Minor advances towards digital manufacturing have been made, while the digitization on other departments still lacks. Which makes it a perfect playground for thorough testing.

After employment of the implementation model through the case study, another tool is utilized. In Appendix A Design science the model by Peffers *et al.* (2008) was shown to consist of a dedicated demonstration and evaluation phase. Evaluation, based upon the performed demonstration must indicate what contributions evolved from the model. In this evaluation stage it will be illustrated how the company will benefit from the improvements established.

4.1. Methodology

Performing demonstration is an important part of the design science by Peffers *et al.* (2008). Through the demonstration phase, one shows that the designed artifact actually does what its intended purpose is. A case study is a tool to test this the designed artifact in an (un)conditioned environment. Case studies can all have different sizes and shapes, depending on the theory/model to be tested (Ridder, 2017).

The design of the implementation model was one established by gaps and holes, according to the categorization of Ridder (2017). This case study research evolves from doing research into a topic and defining the gaps and holes in existing theories, or even the lack of theory. Through this initial theory, propositions or frameworks provide direction and guide the for relevant evidence. Ridder (2017) emphasizes that interviews are the main sources of data collection, but mentions the use of other sources of qualitative data as well. By pattern-matching and establishing relationships within the data, a framework or theory is established.

Especially in the case of "gaps and holes" theory building, single cases (i.e. case study) can serve as a test. It is of upmost importance for this single test to adhere to the clear set of propositions and exact conditions under which the investigation can confirm or challenge the theory (Ridder, 2017). For the gaps and holes-type of theory building case study design is required.

Case study design happens prior the actual case study (Yin, 1981). The design should include the main topics to be covered, the individuals (or roles) from whom information might be obtained and the unit of analysis (Yin, 1981). Furthermore, the collection of data for the use in the case study is also considered within this design. Since this case study follows from a design science (i.e. Peffers *et al.* (2008)), the utility of explaining all steps again is limited. In the practical environment, explanatory case studies are dedicated to the construction and testing of an explanation. Multiple models of utilization to do just this exist, of which "the problem-solving model" is applicable to this study, in which problem identification happens prior to the commissioning of specific research. Subsequently, the case study will test a complex sequence of events, and not merely the testing of a narrow hypothesis (Yin, 1981).

Knowing the origin of the case study (i.e. gaps and holes, and problem-solving) helps to define the execution of the case study. The implementation model, Figure 3.1 already provides a clear overview of the steps to commence. For each of these stages, data is collected to proceed with the remaining stages. Yin (1981) defines several data collection procedures of which 'face-to-face interviews with key informants', 'project documents and memoranda', and 'on-site observations' will be the most prominent in this study. Moreover, in light of the data-based implementation of Industry 4.0, another data source in the sense of 'digitally stored data' like time-series databases, is collected.

Within the practical environment (company) where the case study is conducted, multiple departments coexist. Data retrieval and face-to-face interviewing happens by focusing on the appropriate members of said departments. Throughout the case study, at least the following roles are included via face-to-face contact (at minimum):

1. Supply & planning manager;
2. Warehouse manager;
3. Operations manager;
4. Maintenance manager;
5. Laboratory manager;
6. Raw material purchaser;
7. Production planner;
8. Market coordinator;
9. Factory operator;
10. Warehouse operator.

4.2. Case study

The company is an international player in the agriculture fertilizer market that produces various fertilizers, such as solid (water-solubles) and liquid fertilizers. With a yearly production of 30.500 kilotonnes, with over 1000s of different products and production in 50 countries, the company is considered to be a top league player in the agricultural market. Flagships of the company comprises specialty fertilizers that are sold as premium water-soluble fertilizers. At the basis of these flagships lies the plant in the Netherlands, one of the devoted specialty manufactures within the global organization.

The company's Dutch plant consists of two separate factories that both operate in a different manner. At first, there is the liquids factory, called Substrafeed. This factory comprises of storage tanks, pipelines and a few reactors. The raw materials (mainly liquid) are directed into the storage tanks after which it can be pumped towards the reactors. The final product is then directed to its dedicated storage tank and awaits loading to go to the customer. Since the system is rather optimized and digitized, customers can get their products whenever they want, by simply starting the unloading procedure themselves. The digital system will process the amount of product taken and the invoice will automatically follow.

However, the second factory, meant for solids production, is outdated and comprises over 50 different raw materials and more than 350 products. A large amount of different raw materials find their way to the production site each day. This variety of materials are transported either by ship or by truck, bagged in 15, 25, 600-1000 (Big bag) kg bags or as bulk product. The usage of these raw materials can also range from a few grams up to hundreds of tonnes per day. All this together, create significant fluctuations of in- and out-flow of raw materials and makes it difficult to pinpoint actual and future stocks.

As indicated in previous sections, most of the production inefficiencies can come from various sources. However, raw material supply and production planning are mostly responsible for aforementioned fluctuations in materials. This specifically applies to the solids factory of the company. For that reason, it would be optimal to implement digital solutions into the supply and planning department of the company's Dutch solids factory. By applying the model it becomes apparent how the current process is operating, what inefficiencies exist and what solutions should overcome the present challenges.

In order to keep the competitive advantage, the company already composed a global team of IT experts to address future challenges with regards to Industry 4.0. Now the model is available, we can test its effectiveness by simply using the company's Dutch plant as a case study. After the implementation, the solids factory should incorporate more digital solutions, allowing easier operations and higher efficiencies.

4.2.1. Define

Goal objectives

The focus of the first stage of the model lies on the input steps. These steps provide the basic information required to perform the consecutive steps. The goal of this 'define' stage is to know where to concentrate the efforts initially, to perform the digital incremental steps as efficiently as possible.

The first step in the define stage is to define the goals of the company. As mentioned in the introduction of this chapter, the Dutch plant is part of the international label. This means that the global strategy and objectives also apply to the much smaller Dutch plant. As a result, local initiatives must be shaped towards the global imperatives. However, to enable efficient and effective implementation, local needs are the foremost drivers throughout decision-making.

At first, we study the global goals and planning set by the international organization. This ensures that, on a local level, we adhere to the general vision of the company. As is apparent from the evolve of this thesis, the company is really looking into the opportunities related to the development of Industry 4.0. Organization-wide, data is treated as the new oil and gold, being the world's most valuable resource. Local data is enhanced through the use of clouds, machine learning and IoT architectures to a more global level, thus enhancing the overall competitive advantage of the company.

Not only does the company view these data technologies as potential improvers of existing business, they also perceive the value of data in the sense of new business models and opportunities. Opportunities which they want to grasp through a three-stage journey; (I) shared awareness, (II) predictive analytics, and finally (III) autonomy. These increasing stages of sophistication are driven by applying them to five separate value streams:

1. Plant steering: *stabilize and optimize*;
2. Digital operations: *increase efficiency and safety*;
3. Digital reliability: *minimize downtime*;
4. Mining & robotics: *improve recovery*;
5. Engineering: *digitize engineering processes*.

Looking at the general drivers by Liere-Netheler *et al.* (2018), two of the drivers are particularly applicable to the key purposes of the company. Process improvement is the foremost incentive for the company to make the switch by digital transformation. Through the smart application of several technologies, the global organization sees huge business opportunities by making the existing processes more efficient. Another driver, which is less apparent, is the 'innovation push'. At a higher level in the global organization, directors realize the importance of innovating along with the rest of the industry, preferably at a higher pace. This incentive evolves mainly around picking the low hanging fruits using newer technologies.

As was described in subsection 2.2.2, large corporations behave rather cumbersome. Similar to this description, this company also faces the challenges related to aligning all internal businesses in an identical manner. Consequently, forming the company's global strategy already takes 2.5 years, while still being in the stage of 'proof of concept'. At some of the larger factories, a few small technologies were introduced to test whether the applicability was sufficient for other factories to follow. However, this global approach does align the company's individual business with each other, but does not support a straightforward tailor-made local digital solution. Within the implementation model, the approach is focused on local needs dedicated to the overall -global- strategy.

Therefore, the focus of this case study is to improve the existing local processes (specified to supply & planning) as well as introducing new novel technologies that enhance operations. Equipped with this knowledge, we can continue with the remaining stages of the digital transformation implementation model.

4.2.2. Measure

Business overview

So with the goals and objectives in mind, we can start creating an overview of the current business layout. As in many companies, this company also has multiple departments dedicated to their own task. We can distinguish between supply & planning, production, procurement and warehousing as the four most relevant departments for this case study. Especially the supply & planning department plays a significant role, since they are responsible for the production planning, the raw material supply and a significant part of the order processing.

At first, BPMN's (Business Process Model and Notation) are created of each and every business process occurring within the Dutch plant. The collection of all business flowcharts is a tedious process and requires careful examination and interviewing of the stakeholders inside the company. Oftentimes, companies are adhering to certain standard, like ISO 9001, and have the business processes already mapped as such. All forms of Business Process mapping, like EPC (Event Driven Process Chain) and BPMN, are sufficient starting points to develop the 2D-RAMI model.

Equipped with relatively detailed information, the 2D-rami model can be readily filled. The first focus is to divide sub-processes from the main topic. In subsection 3.2.1 it was already identified that the main processes are forecast (if applicable), assigning suppliers, order processing, production planning, raw material purchasing, storage and production. Each of these main processes consist of various consecutive steps that can confuse one when reading a filled RAMI model. Therefore, subdivision of separate sub-processes help to align the relevant information (i.e. functions, data, communication, etc.) with the respective action taken.

In the case of the company, this subdivision is only required in the case of procurement, where assigning new vendors differs significantly from assessing and negotiating with existing vendors. This distinction, including the rest of the 2D-RAMI model is showcased in Figure 4.1 and Figure 4.2. The model as a whole was extracted from the BPMN flowcharts and finally verified with the corresponding business owners.

With the sub-processes in mind, the second stage focuses on defining the functions. Generally, decisions are indicated in a flowchart by a diamond figure. These crucial decision-making steps, like "how much raw material is required" are all filled in the business process where the decision is made. As a result, the table contains all valuable decisions and already hints upon the information required to make this decision. Since the focus of this case study lies upon supply & planning within the Dutch plant, the majority of the decisions is about raw material inflow, production planning and the decisions hindering these.

Main process	Forecast	Procurement		Order processing
Sub-process	-	**Existing vendor negotiations**	**Assigning new vendors**	-
Functions	What products do we need to make for our customers?	What is the strategic amount we will buy from the particular vendor?	Who is the cheapest?	Do we have the remaining capacity?
	Where do we need to ship our products to?	What is the maximum price we will pay?	Who can fulfil our demands in a short timeframe (delivery times)?	Was it forecasted or not?
			Does the supplier meet our specifications?	What products are required and where do they need to be shipped to?
Data	Market demands based on history (including fluctuations)	Required amount (estimated) of raw materials	Price/volume	Remaining capacity
	Customer requests	Historical and running complaints about raw materials - Vendorrating	Raw material specifications	The order itself - customer specs.
	Upcoming events to country specific (e.g. Chinese new year)	Delivery capacity of supplier	List of amounts of raw materials required	Forecasts
	Available/existing product types		List of available vendors for particular raw material	Existing orders
			Delivery capacity of supplier	
			Raw material specification test	
Communication	Pull market demands from historical data (MS Excel sheets)	Pull required amounts from greensheet (MS Excel sheet via mail)	Pull prices, capacity & specifications from suppliers (email)	Push of order (specs) from customer (phone/email)
	Pull/Push of customer requests via personal contact (mail/phone)	Pull vendorrating from sheet (MS Excel sheet)	Pull specifications from material specialist (email)	Pull of remaining capacity (MS Excel sheets via email)
	List of available product types and their characteristics (MS Excel via mail)	Pull average prices from suppliers/markets (mail/phone/internet)	Pull required amounts from greensheet (MS Excel sheet via mail)	Push of forecasts (MS Excel sheet)
			Push of raw material specification test results (email)	Pull existing orders (SAP)
				Push of orders to tools SAP and Excel (MS Excel)
Digitization	Personal interaction (mail/phone) to MS Excel	Personal interaction (mail/phone) to MS Excel	Personal interaction (mail/phone) to MS Excel	Personal interaction (mail/phone) to MS Excel
				Personal interaction (mail/phone) to SAP
Physical things	Customers stocks	Material usage	Material usage	Factory facility limitations (capacity)
			Product/Production facility limitations	Customer stocks

Figure 4.1: The company's Business Process information visualized in the 2D-RAMI model part 1 of 2.

Main process	**Production planning**	**Raw material purchasing**	**Storage**	**Production**
Sub-process	-	-	-	-
	When do we need to make the product?	What are the volumes we need?	Where do we place the products?	Are all raw materials available?
	What is the best production order?	How much can we store?	Is the assigned location according to the law for that product?	What extra's do I need (e.g. bags, stickers)?
	When do we have downtime?	When do we need it?	How is it booked in the software?	Is there enough workforce?
	What is the capacity?	Where do I buy it?	Does it fit into the warehouse?	Did I use the right/enough materials?
	What prerequisites are in place?	What time does it take till delivery?	Is there a priority location (fast production usage)?	Do I have enough materials to finish production?
	What products need to be made (MTS/MTO)?		Unloading or loading priority?	Is production on schedule?
				Is the product within specs for the customer?
Functions				What has already been produced and consumed?
	Capacity per process	Demand for planned production (short lead time materials)	Storage locations	Material storage locations and stock
	Maintenance planning	Stock levels	Warehouse stocks	Raw material demand depending on current production
	List of orders (MTO/MTS) and required delivery dates (MTO)	Availability of supplier	Amount of delivered raw material/required product	Recipes
	Delivery time of raw materials	Demand of forecasts (long lead time materials)		Effective available time of machinery
	Stocks of raw materials and products	Recipes		Quality data test results
	Prerequisites required for production (stickers, bags, etc.)	Safety stocks		
Data	Required delivery dates of orders	List of assigned vendors		
	Pull maintenance planning (email)	Pull raw material demand (PPA)	Push location to truck driver (SAP)	Push recipes and required amounts (MS Excel)
	Pull orders (Excel)	Pull stock levels (SAP+PPA)	Push of storage locations (SAP)	Pull effective available time of machinery (Evocon)
	Pull delivery time of raw materials (MS Excel sheet via email)	Push of availability and capacity of supplier (MS Excel)	Push of amounts of product (paper)	Push quality results from lab data (Ms Excel)
	Pull existing stocks/prerequisites and future usage (SAP)	Pull forecasts raw materials (MS Excel sheet (history and Greensheet))		
Communication				
	MS Excel to PPA (production planning application)	SAP to personal interaction (mail/phone)	Paper to SAP (adminstrative task)	ERP/SAP to paper (instructions/locations/amounts expected)
	SAP to PPA (production planning application)		SAP to paper (instructions/locations/amounts expected)	PLC to Evocon
	PPA to MS Excel sheet (weekly/daily planning)			MS Excel to paper (quality results)
Digitization				
	Product/Production facility limitations	Material usage	Warehouse stocks	Manufacturing equipment
	Material usage	Warehouse storage	Warehouse layout	Warehouse stock
	Factory facility limitations (availability - maintenance)	Stocks	Truck arrival	Laboratory equipment
Physical things	Stocks			

Figure 4.2: The company's Business Process information visualized in the 2D-RAMI model part 2 of 2.

The information necessary for the functions can be found in the data assessed by the process owner. Particular sets of data, like warehouse stocks, provide the basis allow the business owner to determine the consecutive actions, like purchase of extra materials. Again, BPMN flowcharts clearly indicate what information is retrieved throughout the process. It is these data sets that are shown in the 2D-RAMI model at the data-layer. Within the company various sources are consulted to obtain the required data, which results in a large list of data sets. Examples of data sets are warehouse stocks, production capacities, raw material requirements and recipes of the many products.

With the data sets being known, the focus shift towards the origin from this data. Similar to actual RAMI model, it must be known where the data is obtained and how it reaches the function-stage. However, within the RAMI model, the communication layer refers to the different digital communication protocols that allow data flow by converting from one digital formatting to another. In this 2D-RAMI model, the communication layer presents a similar philosophy; one raw data set, e.g. warehouse stocks in PPA, is retrieved by the raw material purchaser and then converted by experience to an useful data set which is used for the eventual decision-making.

In this communication phase, explicit notes are added. First of all, the information about pulling or pushing is added to indicate whether the process owner has to actively retrieve the data, or is prompted with the data at a particular moment in time. This difference helps to define the working of the algorithm when making the system autonomous at a later stage. A second note is found in the software used. Software is a significant contributor to the efficiency of the communication stage. A lot of software is incompatible with each other which hampers a fluent ”copy-paste” mentality and requires additional actions for it to be useful. Finally the entry is colored in either red (digital/database interaction) or green (physical/personal) interaction. This clearly indicates gaps for the current digitization process and also hints upon which data sets can be made more efficient by introducing digital reporting.

In the digitization phase it becomes more apparent from where the data was created. This stage does not refer as much to the OT and IT interaction (PLC, SCADA, sensor networks) as is the case with the actual RAMI model, but more to physical things like human observation of human interaction are translated into digital software. For example, a customer determine its needs by observing its own stocks and needs. This is essential data for the company, but is not readily obtained since there is no end-to-end integration yet. Therefore, human interaction takes place between sales departments and customers. This sales department then enters the wanted amounts of products into an order system which is directed towards the production planning for scheduling. These translations from a physical source (paper, human, sensoring equipment) to a digital one (MS Excel, SAP) allows data to flow towards the decision-making processes. Especially this layer indicates the speed of the data flow, since human interaction and paper require someone to enter the data manually into a system, which is both susceptible to error and time consuming, making real-time data flow impossible.

Finally, the physical things-layer is filled. This layer is rather confusion in the light of the actual RAMI-model. It is important to define the objects that can be either measured/observed by the human eye or some sort of sensor. With this in mind, you will work towards the ideal situation, where physical objects are measured and detected using electronic devices thus generating real-time data.

As expected, the physical things are hard define outside of the production process. The Dutch plant relies on multiple physical data sources, like customer stocks, production facility limitations and warehouse storage capacities. All could be monitored one way or the other, but are hard to define and capture in a consistent manner. Uncovering these physical objects already helps in describing the digital opportunities in the near future.

4.2.3. Analyze

Key variables

Throughout the overview stage a significant list of data sets was obtained. By combining all these data sets into one list and assigning them to the corresponding business process, a full overview of data is created. As a result, the origin and goal of the data is easily tracked. The full data overview, including all relevant columns, such as category (i.e. main process) and origin is shown in Table 4.2.

Next to the origin (i.e. initially obtained via and verified via) and the goal (i.e. required for), the volatility is noted. This volatility indicates whether the data can change fast or slow, i.e. significantly change within a day. Denominators as dynamic and static describe the pace in which the data set changes. Because the initial focus in on obtaining real-time data, static data is rather trivial when processed in real-time. However, dynamic data can have significant impact on the operations performance and thus require careful, continuous, observation and processing. This means that the extensive list with data sets already reduces to a list with dynamic data sets.

Further delineation is performed by assessing the data sets with a quality team. The objective of this step is to determine the key variables (data) that affect the process performance. Since the model focuses on multiple business processes (e.g. forecast, raw material purchase, production), all should be considered when extracting key variables.

To effectively estimate the effects of each variable, a ranking system is introduced. Table 4.1 presents the 5 categories with which the severity of a slight change in data would cause an effect on the business processes. Each category has an indicative benchmark in both delay and monetary value to allow easier comparison. The delay benchmark specifically helps in the case of time-dependent processes like transportation. The monetary value, on the other hand, expresses the production delay in terms of lost sales. Or in other words: every production hour yields around 10.000€.

Consequence	**Category**	**Delay**	**Monetary effects**
Minimal	1	Few minutes	<5k €
Minor	2	0.5 - 5 hours	5k - 50k €
Moderate	3	5 - 24 hours	50k - 240k €
Major	4	24 - 72 hours	240k - 720k €
Severe	5	>72 hours	>720k €

Table 4.1: Ranking system to find key variables

The relevant business processes for continuous operations are raw material purchase, production planning, storage (raw materials), production, storage (products) and transportation, respectively. For every data set it was imagined that a small change would occur, e.g. remaining capacity reduces with 1%. With this small change in mind it was perceived what effect it would have on all the other processes. In the case of a small change in remaining capacity, this effect would only result in a minimal delay for raw material purchasing and minor delay in production planning, because the production order has to be stretched out or shrunken.

The results of this assessments can be found in Table 4.3. The table is sorted on total effect points, which is easily derived by the sum of all effects. This calculation suffices due to spread importance of each of these business processes. After careful examination, 5 key variables were obtained. Running the model for the first time requires total focus on these 5 key variables. When performing the implementation model a second time, this focus can shift. Assessed effects can either reduce through digital technologies or the variable cannot be improved anymore within the existing system.

Throughout the assessment, it became apparent that the foremost challenge lies within **stocks of raw materials and products**. This dataset is used for determining the production planning, for raw material purchase, for storage processes and also within the production process. Subsequently, the effects are immediately visible through the whole internal process chain when this data is incorrect and/or changed. Within the company, there is already a database containing the current stocks. However, this SAP database requires manual inputs and is only updated once a day depending on the production data. Since this production data is also physically provided (i.e. by paper) to the SAP administrator or not written at all, the administrator has to guess what has been used and errors are quickly made. This results in a discrepancy between actual stocks and digital stocks, which requires periodic physical counting to align the digital stocks with actual stocks.

Data required	Nature	Required for	Initially obtained via	Verified via
Stocks of raw materials and products	Dynamic	Determine needs	Excel/PPA*	Physical counting
Demand on forecasts	Dynamic	Production planning	Greensheet	Forecasting Excel sheets
Maintenance planning	Dynamic	Determine uptime and availability	Internal contact	-
Prerequisites required for production	Dynamic	Determine needs	Greensheet	Forecasting Excel sheets
Quality data test results	Dynamic	Customer requirements	Laboratory equipment	internal contact
Effective available time of raw materials	Dynamic	Daily planning purposes	Evocon (via PLC)	Physical observation
Demand for planned production	Dynamic	Production planning	PPA* calculations	-
Delivery time of raw materials	Dynamic	Determine production order	Supplier interaction	SAP
Material demand depending on operations	Dynamic	Check production schedule	Personal calculations	-
Amount of delivered/required materials	Dynamic	Determine storage location	Supplier interaction	Observation unloading operator
List of orders and required delivery dates	Dynamic	Determine production order	Excel sheet	SAP
Remaining capacity	Dynamic	Determine if new orders fit	Personal calculations	-
Forecasts	Dynamic	Buying long lead time materials	Customer interaction	List of forecasts by markets
List of amounts of raw materials required	Dynamic	Raw material purchase	Internal contact	Excel calculation sheets
Required delivery dates of orders	Dynamic	Production order	Excel sheet	SAP
Customer requests	Dynamic	Determine forecasts per country	Customer interaction	-
Existing orders	Dynamic	Production	Customer interaction	List of orders
Market demands based on history	Dynamic	Accurate forecasting	Personal database	-
The order itself - customer specs.	Dynamic	Determine product spec.	Customer interaction	-
Vendorrating	Dynamic	Strategic procurement	Complaints forms	List of vendors & ratings
Price/volume	Dynamic	Strategic procurement	Supplier interaction	-
Raw material specification test	Dynamic	Check suppliers capabilities	Laboratory equipment	Internal contact
Availability of supplier	Static	Determine lead times	Global procurement	Supplier interaction
Existing product types	Static	Determine forecast per type	SAP	Loose Excel sheet
Capacity per process	Static	Determine production order	Average historic numbers	-
Delivery capacity of supplier	Static	Strategic procurement	Supplier interaction	-
List of available vendors	Static	Strategic procurement	Sourcing	-
List of assigned vendors	Static	Raw material purchase	Global procurement	-
Raw material specs	Static	Select available vendors	Laboratory data	Internal contact
Recipes	Static	Determine required materials	SAP	Bill of materials
Safety stocks	Static	Determine min/max stocks	Excel sheet	-
Storage locations	Static	(un)loading of particular material	SAP	Internal contact
Upcoming events per country	Static	Market fluctuations	Sourcing	-

Table 4.2: All identified data sets (variables) used throughout the business process. *PPA is the production planning application.

Data required	Category*	RM* purchase	Production planning	Storage (RM*)	Production	Storage (products)	Transportation	Total
Stocks of raw materials and products	PP, RMP, PROD & STOR	3	1	3	3	2	3	15
Demand on forecasts	RM supply	1	2	0	2	0	4	9
Maintenance planning	PP	0	3	0	3	0	3	9
Prerequisites required for production	PP	1	1	0	2	0	5	9
Quality data test results	PP	0	1	0	3	2	3	9
Effective available time of raw materials	PROD	0	2	1	2	0	2	7
Demand for planned production	PROD	2	1	0	1	0	2	6
Delivery time of raw materials	RM supply	2	0	1	1	1	0	5
Raw material demand depending on operations	PP	0	0	1	2	0	2	5
Amount of delivered/required materials	PROD	1	0	1	0	1	1	4
List of orders and required delivery dates	STOR	2	2	0	0	0	0	4
Remaining capacity	PP	2	2	0	0	0	0	4
Forecasts	OP	2	1	0	0	0	0	3
List of amounts of raw materials required	OP	2	0	1	0	0	0	3
Required delivery dates of orders	PROC	0	0	0	0	0	3	3
Customer requests	FC	1	1	0	0	0	0	2
Existing orders	OP	1	1	0	0	0	0	2
Market demands based on history	FC	1	1	0	0	0	0	2
The order itself - customer specs.	OP	0	2	0	0	0	0	2
Vendorrating	PROC	1	0	0	0	0	0	1
Price/volume	PROC	1	0	0	0	0	0	1
Raw material specification test	PROC	0	0	0	0	0	0	0

Table 4.3: Ranking of all variables. *RM = Raw materials, PROD = Production, PP = Production Planning, FC = Forecast, PROC = Procurement, STOR = Storage, OP = Order Processing

The second till fifth ranked key variables are **demand on forecasts**, **Maintenance planning**, **Prerequisites required for production (sticker, bags, etc.)** and **quality data test results**. Except for the last, they all have in common that they can significantly affect the production and transportation speed. If the raw material demand is slightly too low because of an inadequate forecast, the production of a particular order cannot occur and is delayed to a later stage. To solve the issue, production planning has to cooperate with production to create a new planning or to find a solution using other materials.

This also applies to prerequisites, who also have a relatively long lead time. The period between ordering bags and the arrival of bags spans around 6 weeks. Since the bags are dedicated to their product group, it can readily happen that the wrong bag type was ordered. Many of the product groups are planned after each other to allow smooth and consistent production capacity. If one of the key components misses in this production, the whole batch must be canceled and delayed to a later moment in time. With speed delivery, it still takes about 1-2 weeks to get the new bags, which makes transportation delay way over 72 hours (highest category).

Quality data results and maintenance planning speak for themselves. The maintenance planning determines the actual downtime of the manufacturing process and thus delineates the limitations for production planning. At the moment, this planning is shared by physical communications once every week. However, throughout the week the planning can change and as a result, only the production department is updated. Similarly with laboratory results. Every batch requires a few tests before it can be shipped to the customer. These quality tests are performed at the lab, who are the only ones in control of their data. After approval of the quality test results, these are taken to the production department by paper, who can then start to transport the products to the customers.

As can be seen in the explanation of the 5 key variables, they share all one thing in common; some sort of physical interaction. For stocks, they are counted physically, for planning and results it is a physical form of communication and for demands and prerequisites it is a time variable that is unknown until physical interaction happens. Altogether, these first three stages of the implementation model highlight the focal points for the company. Even without further, step-wise, processing, a company might have an idea how to improve with this information, not including digital tools. However, the strength of Industry 4.0 lies within data and connectivity, which serves the highest value when being digital because of its fast nature. Equipped with this critical information, we will move forward to the data gathering stage, in order to standardize the way of working and to find solutions for effective production improvements, which is the organization's goal after all.

It is these key variables that you need to guarantee continuous and fluent production. It can be the case that, with ongoing improvement studies, a part of these key variables already have been manipulated over time. However, during analysis such events would show up by the lack of inconsistencies. The starting point of this exercise is ensuring that at least the very basis of the operations is steady and in control. When operating the model continuously, via the feedback loop, new topics will be covered and ways to improve the identified parameters are found. As a result, the incremental process will help development towards a fully data integrated smart factory.

Digital reporting

Digital reporting and OT and IT merger are the two actions to undertake after the variable step. In digital reporting, it is important to convert physical communicated data to a digital format. One of the key solutions for this step is Office 365. Within the company, Office 365 and the accessory Onedrive are widely employed. The tools coming with this are file sharing with a real-time change tracker. In other words; if someone changes something in the file, another person at a different computer would see the change happening immediately. This allows someone to always have the most recent data available when performing his/her task with the corresponding data.

In order to obtain data about the key variables, we must check how we can retrieve the data. In the case of factory-related parameters, like pressure and temperature, this is obviously derived from the OT and IT-side. But observation data (e.g. monitoring the visual representation of the product) and semi-continuous flowing data (e.g. watch transfer on paper) cannot be obtained via OT-connections. Therefore some sort of digital reporting is required.

Within the case study, almost all key variables are already digitally reported. Stocks of raw materials and products is monitored within a digital system called SAP. Every day, someone enters the production numbers of the day before, allowing the system to calculate the used materials. Simultaneously, this person enters the deliveries of new raw materials and subsequently the system determines the remaining stocks. Since this administrative process does not include any forms of waste, digital and actual stocks might become different over time, simply because some deliveries were incomplete or too much of a particular material was put into production, without reporting it. Since this change is only minor, and well-known within the organization, it was considered not to be a major inconsistency - therefore it was not monitored. The digitally available data is accurate enough for performing data analysis, so this set of data was collected through the SAP system. In future implementation loops, it might occur that this deviation between real and digital reported data becomes more prominent - thus requiring to make a digital reporting form in which the warehouse operators enter the incoming and outgoing material flows.

The second variable, demand of forecasts, was also easily obtained via the existing digital tools. Via Excel-sheets and a tool called 'Greensheet', forecasts are made and the according raw material input is calculated using the BOM (Bill of Materials). Since this process is performed solely on a digital basis (i.e. on computers), the collection of this data was fairly simple. Via the production planner, a set of past calculations was obtained, showing the raw material demand based on forecasts for over half a year.

Maintenance planning was a rather difficult one. On the one hand, the maintenance planning was already put into a digital tool; Excel. But on the other, it was just stored locally, making it unavailable for a significant portion of the business. Especially this planning contains valuable information for other departments to aid in their own planning and decision-making. By converting this planning to an Office 365 format, and adding an extra column of information (down-time related to the performed maintenance), other colleagues could use the tool as well, making it more valuable. However, this adjustment did not result in a lot of valuable data within the short amount of time. Therefore, extra data regarding the down time (related to maintenance) was collected via OT and IT merger, which is further explained in the next subsection.

The fourth variable is related to the second one; where forecasts determine the raw material demand. In the case of prerequisites, the same holds true. According to the forecasts, the raw material purchaser purchases materials like pallets, bags, and stickers. In SAP, the planner can find what prerequisites are required to fulfil the demand forecasted. Subsequently, the existing and remaining capacity is calculated via dedicated Excel sheets. When doing the calculations every month, the Excel sheet gets saved and is no longer used. When obtaining the data from the raw materials demand of the last year, we also obtained the prerequisites demand.

Laboratory results, regarding the quality of the product, are the final variable to collect data from. Although this variable lies close to OT and IT merger; you can develop a database in which laboratory equipment automatically enters its results, the current input of laboratory data is a digital reporting one. Laboratory personnel perform the experiment, obtain the data through equipment, assess it, and finally put it into the laboratory database which is stored locally. Similar to the maintenance planning, other departments rely on the information given through this laboratory database. Due to it being stored locally, others cannot obtain the results themselves, therefore opting for a database stored on the cloud (e.g. Office 365). In this case study, the data from this database was obtained via the laboratory manager.

OT and IT merger

In subsection 3.3.3 an overview was made on how to connect Operational Technology (OT) with Information Technology (IT). This section was mainly focused on connecting PLC's of the factory with internal computer systems to allow free data flowing from an unusable source to a useful one. OT and IT merger also works for various other sources which do not involve a PLC or DCS system. There are various stand-alone sensors or equipment found in and around factories that only monitor/measure one parameter which is relies only on human interaction to be taken into account.

At the Dutch plant, there are multiple PLC systems that run continuously with various data sets. All this data is related to the performance of the factory and give useful insights into the operation kinetics. However, the 5 key variables indicated during the input stage did not involve any data about factory performance. Eventually, this data might become relevant when the implementation model enters its second loop, but for now there is no need to retrieve data from the PLC's.

Diving deeper into the 5 key variables, we observe that only maintenance planning is somehow related to the factory's performance. By means of predictive maintenance, this data set can be enriched and also be performed more effectively. However, this is already diving into technical solutions, for which the infrastructure is not in place at all. Therefore, it is not sensible to collect this data yet.

However, production data collected through PLC's is already available within the Dutch plant. In the past, a project was initiated for the collection of process availability data. This was stimulated by the corporate movement towards lean manufacturing. Available data about the performance of the machinery allows to do dedicated data analysis to whatever the need might be, e.g. maintenance down-time, OEE (Overall Equipment Efficiency) or other production related errors.

Ever since the introduction of this system, relatively minor attention was paid to the wide employment of such application. The maintenance and production departments are the foremost users of this novel technology, while other departments like Production planning and Warehouse storage could benefit as much. For that reason, the main focus in this stage is rather aligning the data about the 5 key variables with this data, to see what inconsistencies have affected the production efficiency, and as a result, the production planning and warehouse storage effectiveness.

Since the OT and IT merger can be skipped in this case study does not mean that it is not important in any other scenario. Connection with the PLC and running times of pumps, valves (to specific storage tanks) or other equipment provide very relevant information. When anomalies were found in the larger set of data, e.g. warehouse stocks, raw material demand, etc., something should be compared with it, to know its actual effect.

As example we use the manufacturing of a product in a reactor vessel. Three raw materials are supplied to the vessel in a predetermined order. The first raw material is empty and arrival of replenishment is scheduled soon. With the OT data you can see how long the valves remained closed and how much efficient production time was taken by the truck delay. When this happens multiple times a year, you might want to carefully track these trucks to avoid unnecessary production losses like these. However, if it was a raw materials of which the dosing order could be altered manually, the need for such system becomes much less. In both cases, data extracted from the PLC provide useful information that aid a developed data analysis.

The OT and IT merger in the Dutch plant was established by connecting the PLC to an external server. A bit indicating the operation mode simply send a signal to a set-reset kind of node. As soon as the batch is started this node provides a binary output (i.e. 1) and when stopped this is set to 0. Subsequently, this data is stored in a time-series database which is then converted to a visual representation on a Human-machine interface (HMI). In the solids factory the output (i.e. bags) is measured, since this gives a more refined overview of the status.

In other factories a similar set of data can be acquired. By simply connecting the plc via ethernet, using an adapater if necessary, one could extract information about particular valves if opened, about pumps when activated or any alike data. Storing this data onto a time-series database allows further analysis as was described in subsection 3.3.4. Moreover, this will already give a feeling about the operation performance of a particular module within the factory. Thus, simply adding value to the operations analysis as a whole.

Data analysis

Data analysis in the implementation model can be considered as one of the key steps to take. The first analysis, as in this stage, helps to evaluate the current performance as well as find the obvious existing bottlenecks. A second analysis during the continuous monitoring stage is more dedicated to ongoing practices. The main difference is the inclusion of details. This data analysis stage focuses on the general process data, e.g. daily stocks, and daily deliveries. Insights obtained from this data allows to find common and relatively large fluctuations in yearly operations. Continuous monitoring, on the other hand, applies data analysis to continuous difference at the seconds/minutes scale which enables active intervention and when enough data is acquired, even predictive interaction.

The data obtained in the previous steps is often unconditioned and highly chaotic. As a result, the data becomes unclear and interpretation is highly dependent on the skills of the examiner. Moreover, the cause of particular deviations becomes obscure due to lack of comparison. Initial data conditioning is required to allow comparison between different data sets, and to help smooth data analysis. By adding useful data (i.e. timestamps) and by manipulation of data (i.e. looking for particular raw materials), one could significantly increase the value of data.

With all the collected data, the first step is to align it to a similar output. All the data considered is time-based, which allows for time dependent analysis. Data of the past 6 months (January 2020 till June 2020) was collected and sorted by date. Aligning the data as such helps to combine and compare the different data sources with each other. As a result, the data becomes easier to interpret and causes and consequences can be found more quickly.

Data analysis: Warehouse stocks

After data conditioning a descriptive analysis was done. This analysis targets analysis on complete numerical data sets. It shows mean and deviation, enhanced with statistical information about outliers as well. Conditional formatting is used to mark the outliers on the large data sets. Since most of the data sets contained information dedicated to a specific product group or raw material, it was decided to assess the outliers based on the product/raw material group. By doing so, a clear distinction between different materials was obtained. The distinction uncovered a significant difference in a materials' fluctuation. For instance, one raw material by the code PA165K was consistently fluctuating between zero stock and 48 tonnes. Since it regards a critical component in most of the products, it is concerning that there were days with 0 stock available.

For other materials this fluctuation was on the high side, indicating that too much of the material was present inside the warehouses. Subsequently, an overload of materials is present inside the warehouses, with congestion as a consequence. When finding such a high deviation for a consistent amount of time, one should wonder whether the timing on the material was appropriate. For warehouses with overcapacity, these variations do not precede implications for the process as a whole. However, for a manufacturing site with limited space, these can seriously harm the total performance.

Within the Dutch plant the stocks of 105 different materials were tracked for the first half of 2020. With a data entry every 2-3 days, it becomes hard to efficiently check the stock levels for each material individually. Following the outliers it can already be assessed which materials do not have a consistent stock. This information is ambiguous, because on one hand it offers insights to which materials occupy a significant amount of storage space. On the other hand, it indicates what materials come in large waves. After assessing each material with outliers, both high and low, it is known that the remaining materials have a fairly consistent stock. For these materials it must be checked whether the base stock is not too high, i.e. there is way more material present than required for production. A simple calculation to check the performance is the inventory turnover. By dividing the average demand of each week by the current warehouse stock, one calculates the amount of weeks that production can continue without replenishment. In an ideal world, this number should match the delivery time. That would allow one to purchase the materials as soon as it hits that level. However, to account for delays and other external factors, a safety margin should be applied which differs for each material, depending on its origin. Market shifts occur all the time, possibly resulting in a global shortage of some materials. If one material is prone to these type of fluctuations, larger safety stocks are a wise investment Packowski (2013).

The two values provided the information wanted in this first screening stage. If the inventory turnover was higher than 4 weeks (based on average long lead time) and the average inventory was higher than 20 tonnes (based on 1 truck of supply), the raw material code was highlighted. Finding these materials in a first screening is valuable as they occupy more space than necessary. The second screening is dedicated to the materials with really low inventory turnovers. Some materials had an inventory turnover of less than 0.4 weeks, but also had an average stock of more than 170 tonnes. These are all bulk products and are delivered on a daily basis. Since the turnaround of these materials is high, the safety margins become much higher. Bulk products can often be bought from different suppliers allowing for quick intervention when stocks drain faster than being replenished. For these products as well, it is useful to know current stocks and assess them versus the planned consumption.

The materials of interest are P3215K, P3217K, PA502K, PL597W, PZ001K and PZ015W. These products occupy way more storage space than necessary for guaranteed production. Contrary to these products there are materials that have both a very low inventory turnover rate (< 1 week) and a low average inventory (<20 tonnes). For these products it would be preferred to have a larger safety stock, simply to avoid problems with delivery. The products of concern for this second category are PA134K and PA165K. The final category consists of large stocks (>100 tonnes) with low turnover (<1 week), obtaining PD015K. The average stock values and average inventory turnovers over the past half year are shown in Table 4.4.

Product	**Inventory turnover (weeks)**	**Average stock**
	High storage space occupancy	
PZ015W	5	67.8
P3215K	7.1	45.5
P3217K	7.1	28.9
PA502K	8.9	25.2
PL597W	17.1	20.2
PZ001K	49.4	30.7
	High shortage risk	
PA165K	0.1	3
PA134K	0.3	17.9
	High dependency risk	
PD015K	0.4	173.1

Table 4.4: Storage stock levels performance indicated by inventory turnover and average stock levels.

Data analysis: Forecasted demands

The second data set indicated in Table 4.1, demand of forecasts, was investigated directly after. The long-term demand of raw materials is determined by assessing both historic data and forecasts made by the respective market developers. A raw material purchaser applies her experience to estimate the required amount of material when both historic data and forecast deviate a lot. When doing this, multiple other sources of data are consulted such as current stocks, consumption year to date (YTD) and expected growth compared to historic data. Since the efficiency is highly dependent on experience, a more standardized approach ensures future consistency.

Because it is known that in practice, the raw material purchase is quite accurate compared to the raw material demand, not much production efficiency improvements can be made. However, when doing the descriptive data analysis, it was found that both historic data and forecasts fluctuate a lot. By dividing the demand based on forecast by the average historic consumption you will obtain a factor representing the expected increase in raw material consumption versus historic data. Preferably, this number is close, but slightly higher than 1, indicating that there is a slight increase in demand, thus a higher production is planned. However, due to the nature of the fertilizer specialties market, the demand alters a lot.

At first, the large differences between forecasted demand and historic demand were noticed. To further exemplify the difference it is checked whether such significant changes also applies in historic data, i.e. whether the changing factors for year 2019/2018 are similar to 2020(forecasted)/2019. If the forecast is as accurate as the difference in history, we can conclude that the forecasting is done correctly. Since the system involves many different products that adhere to seasonal consumption, the forecast inaccuracy is known to be high. However, if the differences in actual consumption (based on historic data) is much less compared to the forecasted differences, a part of the inconsistencies can be ascribed to inaccurate forecasts.

A standard deviation taken from the consumption factors represents the significance of the fluctuations in differences each year. For example, in year 2018 there was 2 times more of raw material A required than in year 2017, for raw material B this was 0.95 times and for raw material C this was 1.1 times. The standard deviation of this example is 0.57, indicating how much it fluctuates. A high number indicates that the actual consumption of the raw materials differed a lot from previous year. This difference occurs naturally, due to the shift in sales and by shifting from product portfolio. The average YTD standard deviation from 2017 to 2020 is found to be 0.53. When looking at the forecasted values for 2020 versus the actual consumption in 2019, this standard deviation becomes 0.64. This significant increase could evolve from a large shift in operations (production portfolio) or a new market demand - which are neither the case - or is the result of a inaccurate forecasting.

To test the hypothesis, that current forecasting is inaccurate, can be tested by looking at the forecasted values versus actual consumption. Forecast accuracy can be determined by different approaches according to (Hyndman and Koehler, 2005). One of these methods involve the MAPE (Mean Absolute Percentage Error) which is weighed based on the actual tonnes of production. For each of the raw materials this MAPE number is calculated over the first 4 months of 2020. The absolute error in forecasting ranges from 15% to 405%, as shown in Figure 4.3, indicating that some products are quite accurately forecasted (at 15%) while other are completely out of range (at 405% error). Lewis (1982) mention grades for accurate forecasting. Above 50% forecasting is considered inaccurate, which applies to 25 of the 47 raw materials. These categories apply specifically to the environment that Lewis (1982) investigated, likely very different compared to the fertilizer industry. However, these values provide a perfect initial benchmark to check current performance.

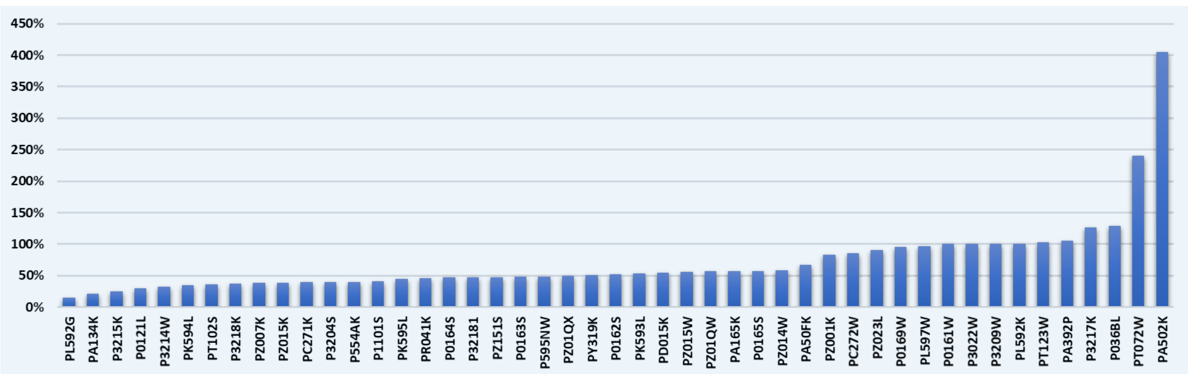

Figure 4.3: Graph containing the MAPE values for all raw materials taken into consideration, i.e. of the solids factory.

With this data analysis it was found that the current forecasts are not in line with the actual consumption numbers. Since it is known that this raw material forecast follows from the sales forecast, extra attention should be directed towards this forecasting procedure. Obviously, forecasting is a tedious process prone to errors, however, more attention is required simply because it affects the rest of the business process significantly. Digital transformation offers various possibilities in this stage, mainly allowing flow of data coming from the customers and integrate it with existing tools.

Data analysis: Maintenance planning
Maintenance planning was the third key variable based on its effects on production planning and production. In the current situation, only maintenance with a big impact is communicated to the production planning department every week. This planning is already providing the frame in which production planning should do its job. However, the remainders of the production planning follows from an average production capacity. When there is limited (small) maintenance required, the production capacity increases and the production will keep ahead of schedule, with raw material issues as result. When a larger amount of maintenance is required than average, the production will fall behind schedule with the transportation issues as a result.

In a digital architecture, such capacities can be determined much more accurately, by using actual average values of typical maintenance actions. By collection of maintenance data (i.e. duration, type of issue, date) one could build an accurate history of down-time. Connecting this maintenance data to the maintenance planning, a more accurate prediction of future downtime is obtained. Subsequently, the production planning can be adjusted as such, diminishing the fluctuations between actual production and planned production.

Since the maintenance planning only includes duration of down-time for a few weeks now, there is not a large database available. However, the monitoring system 'Evocon' described in subsection 4.2.3 can already give valuable insights in the total time required per type of action. Average values can be derived from this data and designated to particular maintenance actions. If this data is also combined with the maintenance planning, it is straightforward to accurately estimate the required downtime for coming weeks when making the production planning. From the existing data set, the delays as shown in Table 4.5 were identified.

Cause	**Time YTD* (hours)**	**Percentage of total**	**Percentage of category**
	Mandatory downtime		
Machinery transition	166	19%	36%
Breaks and holidays	291	33%	64%
	Unforeseen downtime		
Quality issues	19	2%	5%
Inadequate materials	23	3%	6%
Maintenance by tech. service	69	8%	16%
First line maintenance	303	35%	73%
Total	871	35% Downtime	

Table 4.5: Common reasons for down-time based on continuous monitoring via Evocon system, divided into categories. *YTD = Year to date.

The values found when doing data analysis clearly show that there is a large amount of mandatory downtime, 52% to be precise. This downtime consists mainly of breaks (e.g. lunch or specific holidays) which will be insurmountable for reduction. However, the other category, product and machinery transition can be slightly reduced by a more efficient production planning. Having longer runs of the same product will decrease the amount of transitions, thus decreasing transition times.

Unforeseen downtime, taking 48%, is the category in which improvements can achieve the highest effectiveness. Within this category, 4 sub-divisions were identified; product quality issues, inadequate materials, maintenance by technical service personnel and first line maintenance by the operators. For each of these sub divisions, a multitude of reasons was provided which had caused the downtime to occur. The analysis was performed up to machinery level where first line maintenance was further delineated into the different equipment required for production. This helps technical personnel to identify the bottlenecks in the current preventive maintenance planning, which will then further improve the maintenance planning.

In an ideal case, the preventive-corrective ratio for hours is 6 to 1 respectively (Life Cycle Engineering, 2020). As can be deducted from Table 4.5 this is 1 to 4.4 at the moment (i.e. first line maintenance being corrective and technical service being oftentimes preventive). Note that calculating this ratio using the down time reports do not include preventive maintenance hours when the process is up and running, thus slightly magnifying the actual preventive-corrective ratio. When the technical department is provided with information, up to equipment level, provided with its preventive-corrective ratio, they can already dedicate more time to do preventive maintenance, rather than corrective. However, this is hugely dependent on the type of equipment, which will require a more in-depth analysis during the 'continuous monitoring' stage. For instance, some bolt in the production process might break every 100 hours due to its high load. This was known when purchasing the equipment and there is no other solution. If you would add preventive maintenance to this bolt, you might increase the total downtime, just to get a better corrective-preventive ratio. For this reason, the actual downtime of the two combined should also be added.

Adding this information to the maintenance planning helps the planner to give adequate predictions of downtime for the upcoming few weeks. As a result, the production planner is provided with more accurate information, allowing for a production planning that is easier to adhere to. This makes the maintenance planning a more valuable tool and increases the incentive to share it with multiple departments. Simple tools, such as Microsoft Office 365 and Google drive, allow sharing of documents and can be viewed all over the world even though they are being worked in.

The remaining categories, product quality issues and inadequate materials, do not provide any help to the maintenance planners. However, this information does help the production team and raw material purchaser to assess their effectiveness. If these values drastically change, they should interfere with the process and check what effective measure they could undertake. However, that is not part of the current run-through of this model.

Data analysis: Prerequisites

Analysis on prerequisites was found to be much harder. In contrast to the 50 different raw materials, there are about 300 different products. All of these products have their own prerequisites; type of bag, size of bag (15 or 25 kg), stickers, and pallet. Most of these prerequisites must be purchased about a month prior to the planned production. Subsequently, the forecast data is thus even more important than was the case for raw material purchasing.

With raw material purchase, the purchase of excess materials is easily leveled out with the manufacture of other products. However, the bags and stickers are often dedicated to a certain product, which makes relying on a forecast risky. To avoid issues related to these prerequisites, a lot of them are held on stock. This results in a significant storage capacity occupancy purely by the different prerequisites. When looking at the total stock of bags, which is 1.5 million, and the average consumption, 40.600 bags per week, one could derive the average inventory turnover being 38 weeks. Since this high number is mainly dependent on the inaccuracy of the forecast, effective reduction can only be achieved by having a more accurate forecast.

Data analysis: Laboratory tests

Laboratory data turned out to be a tough topic. Thorough analysis of the laboratory data did only result in the analysis of the speed of the quality measurements. At the end of specific production batches, a part of the product is delivered at the laboratory. The lab analyses this batch and checks whether the product adheres to the quality standards of the customers. The time between making the batch and delivery to the lab can take up to one day, but is not monitored. The time between arrival of the samples and analyzing the batch is registered by the analysis database. As a result, we derived that on average it takes 0.64 days to analyze a batch. Subsequently, this means that on average a batch must wait 0.64 days (plus the 1 day delay between production and arrival at the lab) before it can be transported towards the customer. This time infers the time that valuable storage space is occupied by a product that is sold anyway.

Other laboratory data, like typical nutrient contents of some of the fertilizers, was analyzed as well and compared to the raw material data. A likely deviation in nutrient values could occur from picking the wrong material. Such deviation would both affect the warehouse storage data, because another material is missing, and the quality data, since the manufactured product is out of specifications. Neither of the two were found to be consistent with each other, ruling out the likelihood of this deviation. The found deviations (off-spec products) only comprises 6% of all performed quality measurements and were devoted to human errors of which no data was collected. This insight can be addressed by introducing novel technologies, but does not allow us to implement a dedicated technology as of yet.

KPI specification

Concluding the data analysis, it is found that multiple processes are not operating optimally. Forecasts, existing stocks of particular materials and the preventive maintenance planning are current predicates to the inefficiency of the system. For each of these inconsistencies it must be examined what KPI would clearly indicate the systems' inefficiency and aid adequate intervention when being found. Also, it must be noted that the progress of the KPI's is measured over time, which allows for an effective improvement plan at the 'improvement'-stage. All together, KPI's should be selected with care.

The first KPI's are dedicated to the biggest identified thread; forecasts. forecasts are particularly inaccurate and can cause significant issues when the experienced personnel retires or switches from job. During the data analysis, it was already found that one measurement type clearly indicates the systems' performance; MAPE (Mean Absolute Percentage Error). However, this number requires actual intake, depending on existing orders to be calculated. Subsequently, one could derive this number with historic data and historic data only. Having a dashboard with these numbers projected on it would not help anyone to intervene adequately, but only request more accurate numbers at the market forecasters.

Even though this KPI does not enable direct intervention, it does allow future intervention. If the performance decreases this month, the raw material purchaser could immediately check whether the forecast was too optimistic or too pessimistic compared to the actual usage. This could be incorporated for the next month, because there is already a feel for which material might be inaccurately forecasted; thus effectively increasing the safety stock. If necessary, an extra analysis can be done to find which products were forecasted inaccurately, thus increasing awareness at the forecast department as well.

Table 4.4 immediately shows the consideration to be made by the raw material planner. She has to decide whether enough stock is available versus how inaccurate the forecast is, to determine how much needs to be purchased. This immediately infers the KPI that must be measured secondly: inventory turnover. Since most of the raw materials do not have the urgency to be measured, a partition can be made; important and non-important materials. This distinction mainly prioritizes the technology introduction stage. Preferably, one would collect all the data available, thus measuring the KPI for all raw materials. However, sometimes this might not be feasible or financially viable, having to select the one with highest priorities.

The bottom 3 materials indicated in Table 4.4 (PA165K, PA134K and PD015K) are the most important, as these are already low in inventory turnover and thus can infer serious issues in the production process. Having a constant sight on their turnover, based on production planning and actual stock, helps the purchaser to adequately interact with the most volatile products. If the inventory turnover gets below a certain number, a supplier with short lead times can provide the outcome. To avoid unnecessary emergency purchases, one should also add the estimated time of arrival for incoming products. This would mean that two KPI's are established. Inventory turnover and on-time delivery. The first being a good indicator whether there is sufficient material for coming days. The other indicating what safety stock must be used. If a particular raw material arrives late on a consistent basis, you should either increase the safety stock to avoid future problems or demand more more accurate deliveries on the supplier side. Together, the KPI's help the raw material purchaser to make decisions for the coming weeks and allow reaction within sufficient time.

A third KPI is related to the laboratory-quality results. Every company strives for the highest quality standards within its own boundaries. However, this is usually measured by looking at the perfect order performance which represents the amount of orders that have been shipped without complains/damages versus the total orders. By doing so, the company does not critically assess its internal performance. For example, a particular order could have been produced 5 times, because the initial 4 times it did not adhere to the quality standards. Consequently, the manufacturing performance is poor, yet the perfect order performance is excellent (100%) just because the customer has not faced any of the issues. A KPI that actually represents the quality-related performance of the factory is by dividing the amount of samples that turned out to be within specifications through the total amount of samples tested. This KPI aids the operations personnel to be more careful when going below the ideal level.

The final KPI's are dedicated to the maintenance planning. The goal of this maintenance planning is that the production and production planning departments can readily assess the available capacity and act accordingly. At the moment, the amount of preventive maintenance is limited and communication about outstanding maintenance work is minimal. As a result, the required improvement is twofold. Firstly the ratio between preventive and corrective maintenance must be improved to allow for better planning. Secondly the existing preventive maintenance planning must be communicated with the production planning department for more accurate decision-making. However, this second criteria is not measured by means of a KPI and should be incorporated into the technology introduction stage via another route.

In conclusion, four KPI's were identified as useful indicators for the existing process which enable immediate interference with the system. Already moving from the current reaction (i.e. acting upon past issues) to taking action (i.e. acting upon occurring issues). Eventually, after looping through the model multiple times, one will start to implement machine learning and alike, which moves the system to pro-action (i.e. acting upon predicted issues). The intention behind these four initial KPI's, however, is just carefully examining the production process and improving the action-taking to inconsistencies. The four KPI's and their formula are summarized in Table 4.6. For each of the KPI's a typical value was chosen dependent on a benchmark Gordon (2011); Lewis (1982); Life Cycle Engineering (2020).

KPI	**Formula**	**Goal**	**Unit**
MAPE	$\sum(w * \lvert A - F \rvert) / \sum(w * A)$	< 10	%
Inventory turnover*	Actual stock/planned consumption (week)	1-4**	weeks
On-time delivery***	Arrival of truck in-time/total of truck deliveries	> 95	%
Quality	Samples tested on spec/total tested samples	> 90	%
Preventive-corrective ratio	Hours on preventive maint./Hours on corrective maint.	6	-

Table 4.6: KPI selection for identified key variables. w = weight dependent on average usage divided by total usage, A = actual value and F = Forecast *inventory turnover is firstly dedicated to the important raw materials. **Benchmark is product dependent and derived from calculated safety stocks. ***On-time delivery is determined per raw material, but has more focus on the important raw materials.

Technology introduction

Equipped with the information retrieved from data analysis and knowing useful KPI's are the indicators for starting with the technology introduction stage. In this stage, actual technologies, mainly derived from the Industry 4.0 philosophy (i.e. Figure 3.4), are implemented in order to improve the system as was intended in the goal definition stage. The subsequent stages helped to identify critical aspects within the business processes for which technology introduction is key.

Oftentimes, particular technologies are already in place, e.g. PLC and SCADA systems or some cloud technology like the Sharepoint. In the factory of the future, all these are connected and share data accordingly. Depending on the required KPI's, this interconnection must be dominant throughout the technology introduction stage. That being said, the best technology solutions are those that allow easy connection with other modules.

Provided with all information of subsection 2.2.1, one should first identify what technologies are required in order to continuously measure the KPI's indicated in the previous stages. These technologies can be rather rudimentary, like applying a simple sensor on static place that simply communicates via some wireless sensor network. Another example can be found in the communication layer, where some advanced information is shared via an online Office 365 spreadsheet rather than sharing information on a paper. More advanced technologies, such as a machine learning algorithm could also follow from these KPI's, where the decision-making process is made autonomous.

Technology introduction: Forecasted demands
The first key variable to consider is the demand based on forecasting. It is already identified that the current forecasting is providing more questions than clarity. Improving forecasting would mainly involve the data sharing between companies, as the customers can most accurately determine their own consumption. However, data sharing (i.e. end-to-end integration) is out of scope, simply because of the maturity of industry 4.0 at the suppliers and customers-side.

Another option is collecting own data of the customers demand. The agricultural company has a joint venture which is specialized in image capturing of the large fields by means of satellites. With a image capturing algorithm, the farmers can accurately detect what part of the field requires more attention and/or fertilizer. This valuable information has the sole purpose of helping the farmers with their business. However, now it was found that the current way of forecasting is insufficient, a logical link between existing information and inefficient processes can be made. By combining the image capturing technology with the order history of these farmers, one could derive a new algorithm that accurately predicts the future usage (thus orders) of these farmers. Such technology introduction opens up many more business opportunities than initially portrayed, like offering free subscriptions which ensures that the farmer always gets the right materials in time depending on the status of their crops.

So one way to improve the efficiency by means of technology would be the image capturing using satellites. Other ways involve end-to-end integration which is out of scope right now. However, the technology introduction must also be assessed for continuous KPI monitoring. The two datasets required for this calculation are already statically provided digitally, meaning that the physical and digitization layer only need to be considered when continuous monitoring is required. Since actual continuous monitoring does not add any useful information, the KPI itself is lagging after all, the physical layer and digitization layer can be easily disregarded when looking at costs (more than zero) and benefits (zero).

The communication layer on the other hand is an important one considering it is all about having the right data available. Within the company, a forecasting program called Greensheet is available to all market forecasters and the production planner/raw materials purchaser which enables careful examination of the forecast development throughout the month. All that needs to be added is an calculation file (e.g. Excel) that calculates the raw material consumption depending on the forecast extracted from Greensheet. Add to this the importation of SAP data containing the actual raw material consumption and the file is able to show the much wanted MAPE values. Again, some IT architecture could be tailored to automatize this process, but the benefits will be rather low compared to the costs, simply because it does not add any effectiveness to possible interference.

Technology introduction: Warehouse stocks
The second key variable to consider is the warehouse stock. Current warehouse stocks are determined on existing stocks subtracting the consumption (the day after) and adding incoming materials (the day after). All mutations are dependent on paperwork. Therefore, if a wrong material was taken, nobody would find out until the stock is zero while the system indicates some stock. Another issue would be the amounts mentioned on the paper; perhaps less material is delivered than mentioned on the shipping documents. In the current situation, every few months, all materials located on site are physically counted, in order to align the digital environment with the physical environment again.

Technology solutions should mainly be found in the physical/digitization layer, as this is the clear imbalance causing the inconsistencies. Using paperwork to communicate between separate departments should be avoided at all costs, and simple solutions such as the Microsoft Office 365 package could already avoid unnecessary handwriting mistakes. Add a Human Machine Interface in the form of a tablet and one can easily indicate how much was added or withdrawn from a particular material.

However, such technology introduction is still rather old-fashioned, and newer technologies like bar codes and RFID tags can offer good alternatives. Most of the bags have barcodes printed on them, which allows easy adoption of bar code scanners. All bags are transported using the forklifts on site. Add a bar code scanner to each forklift with the simple button '+' and '-' and a more sophisticated warehousing system is reached. The third option, RFID tags, will be more tedious, as the RFID tags are manually applied to every bag/pallet on site. For incoming materials this is unfeasible as of now, simply because the suppliers do not add the tags themselves yet. For our own products this can be a good option, but this does not relate to the key variable at stake.

So two serious options can be considered when identifying the warehouse stocks. Bringing the third KPI into play, on-time delivery, two KPI's can be measured at once when designing the technology in a clever manner. Since both an HMI system as a barcode system can aid the on-time delivery measurement, no such distinction can be made. Other trade-offs were identified using the information provided in subsection 2.2.1 and in-house experience about current way of operations. The pros and cons for both options are shown in Table 4.7. Since the basis of these two KPI's rely on continuous

HMI	**Barcodes**
	Pros
Only a few tablets with internet connection required	Convenient to operate
Easy to maintain (Office 365 software)	SAP already aligned with multiple bar code systems
Opportunity to switch programs (Acces, Excel, etc.)	Enhanced accuracy
	Cons
Not able to continuously import Excel into SAP	Barcode equipment must be installed on forklifts
Still sensitive to errors	Install barcode operating system
Sensitive to break down	Barcodes not available on all raw materials

Table 4.7: Pros and cons for the two options to consider for continuous monitoring of warehouse stocks as well as delivery times.

monitoring, and the once option requires a completely new system to be tailor-made (Excel importation to the existing SAP modules), the choice can be made without inferring any costs. The Barcode system is simply more convenient to use and install and is the only option to keep continuous track of the KPI's. Moreover, such system is also viable organization-wide, which enables other locations to reap the benefits of such sophisticated system.

In this case, the barcode scanners eliminate the paper work, manual importation of mutations, and the redundancy of communication. Therefore, replacing the existing physical, digitization and communication layer with one envisaged in the Industry 4.0-philosophy, able to cope with future demands and flexibility.

Technology introduction: Maintenance planning

Maintenance planning is the final key variable to consider in the technology introduction stage. As indicated in Table 4.6, an important KPI is the preventive-corrective maintenance ratio. Preferably, this ratio fluctuates around 6, suggesting that most of the down-time is dedicated to preventive maintenance. Which on its turn, illustrates that most of the maintenance was planned. This KPI, however, is already fully digitized, since the data can be gathered from two different sources already. One being the spent hours which are filed in the SAP maintenance system. This number clearly indicates all the time spent by the maintenance personnel, which also includes so-called 'uptime' hours, i.e. when the factory is running. It is obvious that the number including uptime hours is the one that must be close to 6, because preventive maintenance does not always include downtime, but corrective maintenance does.

That being said makes the second option for KPI monitoring less relevant. Which is the Evocon system that measures whether the manufacturing process is running or not. Consequently, the Evocon data enables to look at the preventive maintenance from another perspective. It helps to capture when a particular downtime starts and when it stops. Such information is very valuable when having a higher preventive maintenance ratio, simply because it allows for better planning. By taking the average of some preventive maintenance action, one could already align the production planning accordingly, rather than making an insufficient planning.

In the previous stage it was mentioned how important sharing of the maintenance planning is. Currently, the maintenance planning is documented in an Excel sheet, which is printed every two weeks and discussed with the production planning department. For most of the preventive maintenance it is not known how much time they take, nor how long the factory will be out of order. Capturing these values from the collected data helps to further enhance the maintenance planning. Simultaneously, the maintenance planning can be communicated in a better manner. In line with the Industry 4.0-philosophy, one could use cloud solutions to easily spread the planning without any further implications. As a result, the production planner can see the current outstanding maintenance activities and act accordingly. A simple cloud solution, which is already in place, is the Office 365 software package. Converting the existing Excel sheet into one on a cloud environment, allows easy adoption by the other departments as well.

Technology introduction: Laboratory tests

The laboratory tests can be a crucial part of the manufacturing operations. Some of the products must be examined for their quality (according to specifications) before they are shipped to the customer. Having an adequate and accurate measurement is key in these cases. For that reason, a laboratory on site has the sole purpose of analyzing these samples for their specifications. After a sample of a particular batch is handed over, the laboratory technician is carefully withdrawing a certain amount and puts it into pre-defined analyzing equipment. After the sample was analyzed, the laboratory technician examines the values and checks whether these are according to the wanted specifications. Finally, he enters these values into a database to ensure that they are retrievable at a later stage.

An initial improvement in this process would be the introduction of IoT specifically for laboratory equipment. Currently a human interacts with the laboratory equipment after which he interacts with a computer. This could be completely removed by using IoT laboratory devices that connect in real-time with aforementioned database. As soon as the analysis is finished, the laboratory equipment sends the data to the database (automatically) and is then shown in real-time on the computer screen. Using a few extra rules, depending on the pre-defined specifications, and the system clearly shows whether the product is according to specifications or needs to be reworked. Not only does this reduce the human-intensive operations, it also enables a future in-line quality measurement which utilize in-line sensors or laboratory equipment rather than the manual collection of samples.

Continuous monitoring

Since the actual implementation of said technologies did not take place within the time constraints of this case study, no actual data was collected through this period. However, to showcase the proceedings of this case study, if enough time and resources were available, the remainder (continuous monitoring, improve and evaluate) are described superficially using examples from the previous stages. Moreover, these descriptions are discussed with the practitioners to ensure careful and accurate examination of the remaining 3 steps.

As was indicated in chapter 3, the continuous monitoring stage is focused on using technologies implemented and carefully examine the corresponding results. Since the use of technologies is widespread; with the implementation of Machine Learning (ML) you are monitoring the effectiveness of said technology by checking whether the decisions made are in accordance with the intended purpose, where IoT introduction is more focused on monitoring whether the right data is flowing in, as well as monitoring that data to use in the decision-making processes.

During the technology introduction stage, three major technologies should find its way into the manufacturing practices to improve performance and to aid innovation push, as was the goal of the company. The three technologies considered are: (I) image capturing, (II) bar code scanners for measuring warehouse stocks, and (III) preventive maintenance-based maintenance plans. All three serve a completely different purpose, but address the corresponding underperforming KPI's in the right manner.

The image capturing technology is already available with in-house knowledge. By enhancing this technology using a similar machine learning type of coding, we could derive a farmer's needs in terms of fertilizer agents. By sorting this 'demand' data per country or per product type, allows the forecasters to determine how much their customers need based on actual representative data, rather than 'a gut feeling'. Moreover, these algorithms can even extend such that, on the long run, the algorithms determine the forecasts themselves.

It is known that not all customers are apparent, some of the customers buy their products at distribution locations (i.e. small amounts), others work with inside a building (greenhouses) which makes image capturing less applicable. However, even though it applies only to a part of the customers, forecasters will become more aware of future consumption by just keeping track of the major consumers. As a result, the production planner will obtain more accurate forecasts, therefore seeing the MAPE values drop. Steering the forecasters' perception also becomes much easier, because these MAPE values provide helpful insights for the forecasters showing that their job is done correctly or not. Especially the fluctuations of these values, driven by the image capturing technology, help to improve the process over time and making it less reliant on the experience of local personnel.

The bar code scanners cover a completely different field of technology. Since these scanners can be considered to be on the 'primative side' of Industry 4.0, due to being just basic sensors, their continuous monitoring stage is much more straightforward. By accurately capturing the ingoing and outgoing flow of raw materials and products in the warehouses, production planning and raw material purchasers can make far better decisions through the real-time nature associated with it. Accurately knowing how much of material X is available for the coming weeks helps in choosing whether the material has to be purchased from a distant location or via a quick, often expensive, near location. Knowing the average delivery times and on-time delivery of said supplier, supports the production planner in choosing what products are produced in what week.

Other than actually using the continuous inflow of data, also comes the monitoring of the KPI's related to warehouse management. The goal of this continuous monitoring stage is to see how the business process can be improved (or introducing new business opportunities) by assessing the performance using novel technologies. Through careful evaluation of the KPI's over time, one can detect anomalies and avoid these exceptions from happening again. For example, the production of product Y requires raw material Z. Raw material Z has a similar neighbour called raw material Zi, which is nearly the same in composition. Due to inattention, the operator takes raw material Zi for product Y, but reports that he took the right raw material Z. Since the raw materials are similar in nature, the laboratory results do not discover that a different material was added. No one finds out about this misunderstanding up until the production planner scheduled a production using material Zi, thinking there would be enough, but just finding out that the storage location of said material is empty. In the case of bar code scanning, the production planner would have noticed this reduction much earlier, since the inventory turnovers of said product diminishes in a much faster rate than anticipated. Not only can she interfere at that moment; to avoid unnecessary quality problems, she can also propose a plan for the improvement stage where materials Z and Zi are no longer next to each other.

The preventive maintenance planning is the third 'technology' to consider in the continuous monitoring stage. Although the tool is not novel itself, the use of appropriate cloud platforms is. By sharing the data throughout the business processes, different stakeholders are aware of the ongoing and upcoming maintenance and act accordingly. Particularly the production planning benefits from knowing the real-time maintenance schedule, including having an estimate on the duration of it. Nowadays, a lot of the maintenance happens either corrective - when the factory cannot run due to an error - or when the production is ahead of schedule and allows the technicians to do their job. However, this way of working might cause the moment of interference - by the technician - to be inefficiently chosen. For instance, if the production planner is aware that a particular piece of equipment must be replaced, she can effectively dedicate some time in the production planning to this, by scheduling other tasks or production not using that particular equipment. As a result, the production planning becomes more accurate. A part of the maintenance is actually planned and the preventive maintenance increases, because enough time is dedicated to preventive maintenance thereby reducing the corrective maintenance. The continuous flow of data altering the KPI also helps the planner to see how effective the maintenance is planned and whether she has to adjust the time specific for maintenance.

With regards to the laboratory IoT introduction, a significant part of the operations are automatized. The direct connection between laboratory equipment and the database allows multiple people to know the current conditions. For example, the shift supervisor can see that one of the products being made is not within its specifications. Consequently, he can directly stop the manufacturing process and check for problems and solutions without interference. The multiple human layers (interpretation of results, entering results into database, etc.) currently hamper quick interactions like this.

4.2.4. Improve

Improve

According to the information and data collected through the continuous monitoring stage, business processes are improved. Especially in this business case, where operations improvement was considered to be one of the major goals, the improvement stage is considered to be a major contribution to the implementation process. Since actual implementation of different technologies cover diverse time paths, the improvement stage has the most obscure time path. As soon as the implementation is realized, data is being used to interfere with occurring inconsistencies, already participating in the improvement process.

Depending on the interventions that were performed, consistent improvements might find their way to introduction as well. If a particular deviation happens frequently with a significant down time as result, managers will address these underlying causes using the clear information obtained through the interconnected digital technologies. Solutions introduced in the improvement stage are generally pragmatic in nature, like the assigning distinct storage locations for alike looking raw materials.

Especially the use-case of the image capturing technology enhanced for forecasting purposes could infer multiple improvements. Forecasters will have more data to base their 'guesses' on, typically improving the forecasting processes. Simultaneously, data converted to MAPE-values for products help them to identify what products are currently over- or underestimated. If a diminishing trend was found in Product X, they can take countermeasures by either communicating with the customers why their demand decreases or increase the power on sales to counteract the fall. When the reason for the fall of a particular product is the result of continuous delay in delivery, forecasters can emphasize the importance of in-time delivery thereby improving the business processes. These MAPE values are much likelier to provide these insights, simply because personnel is pointed at a high inaccuracy, while diminishing sales of a particular product does not say anything about the expected reduction of said product. In the case of MAPE, the expectations are included through the forecasting behavior.

For warehouse stocks the improvement-stage shall be considerably shorter compared to the forecasting variable. As was indicated in the 'analyze'-stage, warehouse stocks are on point and do not cause a lot of issues at the moment. In the near future, things might change due to changing markets and shortage of particular materials. In this case, knowing the actual stocks and inventory turnovers help the purchaser to make considered decisions in utilizing the best of the warehouse capacities.

Another improvement can be found in the HP ink delivery example. If the warehouse stocks are measured accurately - by the means of bar code scanners - this data can be shared with the different suppliers. Based on the strategic procurement agreements that were made, suppliers can see our inventory turnover and remaining stocks. When the stock levels get into the 'dangerous' zone, a pop-up on the suppliers side causes an automatic replenishment of said stock, significantly improving the process by eliminating the time spent on raw material purchase.

For maintenance planning the improvement options seem unlimited. Currently, the preventive-corrective maintenance ratio is far of 'good'. By just planning accurately and assigning the right description to the performed maintenance (i.e. preventive or corrective) already significantly improves the existing maintenance process. However, to further evolve the maintenance capabilities, a technology like predictive maintenance can be introduced. Predictive maintenance is the use of sensors that measure things like vibrations of equipment, which can - with use of historic data - notify users when particular equipment is about to break down. When knowing this in time, the preventive maintenance can be planned on time eliminating nearly all corrective maintenance.

4.2.5. Control

Evaluate

The evaluation stage comes at the end serves two purposes: firstly, it describes the lessons learned throughout the implementation process to avoid them from happening in a second loop, and secondly it is a controlling stage in which the implemented technologies are evaluated and it is checked whether they are used correctly and serve the right purpose. Due to the elastic time span of the improvement stage, this evaluation can be performed while improvements are still being introduced.

As explained before, in this case study there was no actual implementation or improvement made. However, the steps towards implementation were performed and these are considered to be the main contribution of this thesis. The remaining steps, of which evaluation is one, are supporting the Industry 4.0 implementation and can be seen as enabling processes. With this in mind, a few remarks can be made about the evaluation/controlling stage that can be included in a possible second loop.

First of all, some interviewees mentioned user satisfaction as being one of the major pillars for successful adoption. Everyone mentioned a different way of evaluating their implementation performance. However, one clearly stood out among the others. One interviewee mentioned the use of satisfaction buttons, similar to those which you see at toilets in the airport, where users can grade the product with 4 (or more) buttons ranging from really satisfied to dissatisfied. By simply prompting the grading system at random times and at random pages/software/technology, they were able to see what was working properly and what not. When seeing multiple dissatisfied users, they entered the conversation and found out what was not working in line with their expectations and improved it.

A second pillar is found in learning and growth. Training the users to use the system is a critical step for useful implementation. As soon as the product or technology is launched, all users should know about it and be ready to use it. A particular good habit is the use of beta-testing, where potential users are involved in the development process. In return, the developers get useful insights in how the users 'use' the system and users can express their specific needs which might have been overlooked by the development team. Through this type of beta-testing users are already trained in using the new system and can suffice with a little follow-up training. A well established methodology within the industry; Management Of Change (MOC), is particularly good at tackling this issue of training. By using a stage-gate process, the implementation cannot be finished, nor used, without the enclosement of proper training.

Although the evaluation phase focuses most on the technology implementation, other stages can be reviewed as well. In this case study, the 'quality team'-approach was used to define the key variables. After defining all data sets being used, we looked at their respective effects on the rest of the process. The ones with the highest effects on the resulting down-time were considered to be the key variables. Despite this being true, we also found that some of the found variables were performing really well. Both the raw material purchase and warehouse stocks variables were quite constant on average. This positive result is the result of the efforts of the people responsible for this job, due to their immense experience in the field. Through the key variables, this trait was acknowledged, but also reflected upon the existing business. If one of the colleagues responsible for this job would retire or drop-out, the experience will no longer cover the lack of information and the results will drop immediately. If looking at this, the key variables were chosen effectively, as the resulting picture turned out to be really valuable. However, the aim of the model, according to stage 1 'define', was to improve efficiency which is not really the result of this. For that reason, the next loop might include a new way of finding the key variables; based upon the continuously occurring errors, via the Pareto principle, simply to target the largest efficiency drains.

4.3. Summary

This chapter described the utilization of the implementation framework by performing a case study at an agriculture fertilizer manufacturer. Each of the stages defined in chapter 3 were executed either physically or by means of simulation/explanation. Through the initial stages of define and measure it was assessed which part of the supply & planning process are open for improvement according to the Industry 4.0-scope. The company-wide scope on digital transformation was delineated by using key phrases, thereby aligning it with the local needs. A 2D-RAMI model provided the outlay for dividing a complex interrelated business process into smaller comprehensible pieces.

The 'Analyze' stage dove into the particular RAMI layers obtained at the 'Measure' stage. Analyzing the key variables showed where to focus diminishing one of the identified barriers, having a clear business case. Knowing the key variables initiated the collection of data from multiple sources. The data was then conditioned for a deeper data analysis. Various 'concerning' deviations were found in the data, indicating that improvements are still to be made. According to the discovered inconsistencies a few KPI's were assembled that enable quick and effective insights into the performance of the operations as a whole. An Industry 4.0-related technology was then assigned to provide the data or information for the KPI of interest after which continuous monitoring could happen.

Depending on the insights obtained from the new incoming data and the continuous monitoring of the KPI's, it was time to actually improve the operations process by eliminating recurring inconsistencies. Since the technology introduction was just simulated/explained, it was only possible to describe the improvement and evaluation stages using the experience of the interviewees.

5
Discussion

In this chapter we discuss the relevant outcomes of the study by looking at the development of the model (i.e. chapter 3) through the literature review and interviews (i.e. chapter 2), and the subsequent utilization of said model through the case study (i.e chapter 4). This chapter serves as the evaluation stage in the model depicted in section 1.4 by Peffers *et al.* (2008) and will have a critical look on the performed case study, its implications and other shortcomings.

5.1. Industry 4.0

The first discussion is dedicated to the Industry 4.0-aspects of the implementation model. This model was constructed with the intention to increase the adoption rate of Industry 4.0 and to aid practitioners with a straightforward Industry 4.0-implementation model. The model turned out to be useful and capable of the implementation of the Industry 4.0-concept as was described in chapter 1. However, even though the model fulfils its intended purpose, one could argue that the opposite does not hold true anymore. In other words; does the implemented solution require the Industry 4.0-concept or can you perform the same improvement without using Industry 4.0-concepts? The latter would make the implementation model more widely applicable, but abandons its intended origin.

Such question arises from the foundation of this model; namely the DMAIC and quality improvement model by Aitken *et al.* (2004). Both are widely employed within the manufacturing industry and are already serving their purpose for decades, even without Industry 4.0. Subsequently, going through these models does not require any novelty or sophistication similar to the Industry 4.0-concepts. This indeed means that these two concepts cannot be labeled as Industry 4.0-implementation models, nor can the collaboration of the two.

However, in this thesis special care is taken by interviewing multiple practitioners. These practitioners had their own way of working, shaped through years of experience. Casting this experience into a mold, a standard procedure to improve processes (i.e. DMAIC), does actually change the context and applicability of the resulting model. By applying a different nature and approach alters the result significantly. For example the 2D-RAMI model is clearly different to the standard DMAIC-measuring stage where one is investigating a problem superficially. In case of the 2D-RAMI model multiple aspects related to the Industry 4.0-concept (connectivity, communication, and physical things) are distinctly mentioned to decrease the complexity of the system, thereby uncovering opportunities. Without this Industry 4.0-concept approach (i.e. the actual RAMI model follows from the emerging Industry 4.0-philosophy) a completely different solution - likely not future-proof - would have been proposed.

Also during the technology introduction-action this delineation between a regular quality improvement model and this Industry 4.0-implementation framework becomes visible. A set of 13 enabling technologies were identified that all infer different subsets of technologies (i.e. AIDC with bar codes and RFID). By showing what technologies could aid the operations process at what layers of the RAMI model, we are not just introducing just the Industry 4.0-related technologies, but we also provide a portfolio that is future-proof and aligns with subsequent industry 4.0-related technologies.

Nonetheless, as was described in chapter 1, the concept Industry 4.0 is ambiguous. A clear - and globally accepted - definition of the term is still to be defined. Our definition of Industry 4.0: *"Industry 4.0 is the fourth manufacturing revolution that evolves by companies implementing novel technologies in a smart way to improve current operations in the realm of autonomy, efficiency and social responsibility"* (cited from subsection 1.1.1) describes the expected implementation philosophy, which is in line with the implementation framework.

5.2. Model construction

Through the conduction of a desk research, i.e. literature review, and a qualitative research, i.e. interviews, an implementation model was developed. Despite the fact that Industry 4.0 and digital transformation are widely used topics within the industry, their applications are rather focused. Very few articles mention the use of Industry 4.0-related technologies in the sense of raw material supply & planning. Topics like smart supply chain, smart factory and predictive maintenance are far more popular, but therefore limit the scope applications significantly. Through the development of this model, aforementioned topics get submerged into one by addressing the boundaries of every manufacturing businesses; the interaction between suppliers and customers, including the operations process in between. This not only provides an useful use-case for businesses yet to digital transform, it also combines the complexity of intertwined business processes and the utilization of novel technologies; capturing its full potential. However, constructing such model does not come without limitations, assumptions and constraints.

In the first chapter, chapter 1, it is explained how this model should aid complex factories in their digital transformation process. Complex factories, in this thesis, is a label put on manufacturing businesses that involve a significant amount of different raw materials and products. This notion already eliminates a huge category of bulk manufacturers. The main difference between the two is the complexity of the supply & planning process. For bulk manufacturers the production planning is already known for upcoming year, because there are generally just a few products being manufactured. Complex factories (commonly known as specialty manufacturers), on the other hand, have to deal with multiple orders coming in, requesting different products, therefore requiring specific raw materials, and all of that on a continuous basis. As a result, they have to deal with forecasts and predictions, which makes the whole operations more tedious. Minor fluctuations in orders can already cause the production of products that will not be sold, resulting in high losses in terms of costs. Thereby indicating the need for more accurate data and decision-making assistance. Thus making this digital transformation model only applicable to a distinct set of businesses.

Since a substantial amount of businesses utilize the lean, six sigma and agile-philosophy to improve their processes, the introduction of a new 'methodology' that is yet to be thoroughly proven, is not a welcome one. Many of these businesses still struggle with taking advantage of the techniques incorporated with lean, six sigma and agile. Therefore, the link between Industry 4.0 and lean must be strong to aid smooth and straightforward adoption. Multiple researchers described the different ways of how to connect lean and Industry 4.0 (Rosin *et al.*, 2020; Mrugalska and Wyrwicka, 2017), but all of them tap into how the technologies impact the lean principles, and not the other way around. In this study it is proposed to use a Six Sigma method; the DMAIC structure, to implement the technologies related to Industry 4.0. This controversy view on the topic should bridge between the business' current practices and show how these can result into future practices (i.e. digital transformation). However, this proposal is based upon careful alignment between existing research and current practices, and identifying a gap in between. Therefore basing it just on empirical evidence, with no records of actual utilization in this way. The reason to opt for Six Sigma rather than lean and agile on this matter is the focus of an actual improvement process, which both Lean and Agile lack (i.e. waste elimination and making existing processes smoothly connected, respectively).

In both the literature approach and the qualitative practical research emphasis was put onto the parameters side. This perspective was twofold; first the parameters are good indicators of the performance of business processes, and secondly the investigation of the parameters help to understand the interrelation and execution of different business processes. With this in mind, two existing methods for business performance management were found: SCOR and BSC. Since both of these management models address the topic of this research 'raw material supply & planning', their application is particularly useful. However, since these methods are complex and sophisticated models themselves, they were not incorporated completely. Only core aspects, like the business model identification and the KPI selection, were taken from these two models. Consequently, the interrelationship established in these models is breached which makes them function differently. Using the implementation model should therefore not be considered similar or substitutiary to the SCOR and BSC approach, but more like a complementary model.

Probably the biggest limitation of this study is related to technology research. This study is conducted in 2020, and is therefore limited to the technologies and innovation available at that time. Since Industry 4.0 is a hot topic at the moment, and new technologies and innovation might get introduced at any time, the technology study could become obsolete really fast. Though the technology list is considered extensive at this time; it includes all aspects of Industry 4.0 according to the literature investigated, it could be only a minor fraction of the final Industry 4.0-technologies list. For this reason, it is recommended for practitioners to look out and actively examine the ongoing research into new technologies, to keep in touch with the growing capabilities of innovation.

In two different studies, i.e. interviews and literature study, it was investigated what kind of adoption barriers are currently preventing businesses from reaping the benefits related to digital transformation. Through these studies, a multitude of causes were identified, comprising reasons like lack of courage, lack of talent, and people management. Through the design of the implementation model, solutions to a multitude of barriers were developed, like the evaluation part to cover people management, and the lack of standard options for factories by providing a guideline how to employ modularity in order to decrease the needs for 'a standardized approach'. However, some of the barriers have not been addressed through the implementation model, due to them being unsolvable (yet), or because of its applicability to very specific cases. The barriers that were not addressed, and need further investigation in future research are the following:

1. Chaos of available data;
2. Asynchronous working of architectures;
3. Contractual issues with sharing data beyond the companies' boundaries;
4. Software related issues, like Excel being outdated for Bigdata;
5. Horizontal integration (information share along the business process);
6. Cybersecurity;
7. Concerns about data ownership.

Obviously, a lot of stories and research evolve from the successful implementations of Industry 4.0. Consequently, the majority of case studies and interviews provide insightful information about how to correctly implement Industry 4.0. However, a lot of lessons learned - being the unsuccessful stories - are kept quiet and were hard to discover. The implementation model includes a loop and evaluation stage, thereby providing practitioners grip on the situation and allowing them to improve by their own lessons learned. Nonetheless, knowing more implications from predecessors help to shape the model around these pitfalls preventing the same mistakes from happening over and over again. Future research should dedicate substantial efforts in identifying these pitfalls and expressing them at the corresponding stages.

Multiple researchers focused on the different stages of Industry 4.0 adoption, mainly identifying three stages: (I) Simple implementation (e.g. cloud-based working and implementing a few sensors), (II) Advanced implementation (e.g. automation and Artificial technology), and (III) Smart manufacturing (e.g. autonomous manufacturing and end-to-end integration). Although this is valuable information for a company to understand the future steps to take, it does not provide a road map to actually get to these stages. By looking into models that describe the improving nature of manufacturers by incrementally progressing through different stages, we created a solid foundation for the digital transformation implementation model. The continuous quality improvement model (Aitken *et al.*, 2004) had a significant amount of similarities with the implementation process described by experienced practitioners. As a result, the link between the two was made fairly straightforward. However, the initial aim of the improvement model is quality improvement, while the Industry 4.0 implementation covers - along with quality improvement - a wide range of other goals as well. By applying minor adjustments, like the goal definition stage, we taper the implementation model to the spacious dimension of needs but thereby introducing another variable that could increase the complexity of the implementation process. In future studies, the perception of this complexity and its possible side-effects must be evaluated.

A huge advancement in aligning existing literature with practical use-cases was the introduction of RAMI. By describing the novelty of several technologies using a structured reference architecture helps both researched and practitioners understanding each others' world. Since the current RAMI model does include, but does not describe, the relevant business processes, we made an adjusted 2D-RAMI model. This 2D-version enables users to effectively draw their current business structure without having to dedicate too much time to details (on the third dimension; hierarchy). This modification is considered to be one of the major attributions in this implementation model by creating a clear framework in which the existing and possible future business is described. Without diving into too much detail, as is the case for BPMN (Business Process Management Notation), this modified model characterizes the main features of the business.

The data analysis description is one that deserves more attention in future work. In the current set-up data analysis is a descriptive one, aiming majorly for the average, standard deviation, and outliers. As a result, these simple analytics will provide the user a sense of understanding how the processes and data relate to each other. However, the subsequent stages where attention shifts to correlation, causation, and alike demands a far more intensive background and experience with data analysis. Therefore, in the current set-up, the far-fetched data analysis which yields the best results, is only devoted to the ones with substantial experience in the field. It is recommended that future work includes specific data analysis strategies dedicated to the specific type o data sets possible (i.e. nominal, ordinal, interval and ratio).

A final shortcoming is ascribed to execution of the model. Timing is an important aspect of effectiveness, one of the model's prominent characteristics. Only a few of the stages have a clear end-point, like only obtaining 5 key variables or sticking to a maximum of 5 KPI's. However, the remaining steps can continue endlessly, depending on the level of detail the user wants to include. For example, the 'data analysis' stage can differ from capturing a few averages up to a full statistical analysis including all sorts of correlations and causation. Similarly, the 'business overview' can dive into full detail, describing what data is stored in what cell of a spreadsheet, while providing a general overview of what kind of data is used would suffice as well. Through the execution of the case study, a general feel of the intended purpose and time duration of the model should be given. However, future studies can enhance the existing model significantly by clarifying the intended result of each stage.

5.3. Case study

Not only the development of an implementation model comes with limitations, also the subsequent case study can only test the model up to some degree. Especially the stages that involve input from different stakeholders turned out to be difficult. During the progress of this study, a global pandemic called COVID-19 evolved. This pandemic hampered internal communication significantly and resulted in a lot of phone- and digital telecommunication-calls rather than having free-flowing face-to-face contact. Although the impact of the pandemic on this study is perceived to be limited, it must be noted that it did alter the - otherwise fluent - communication channels.

The first implication around the conduction of the case study lies in the participating nature of the company's location. The case study was executed at one of the smallest factories (in terms of production output) of the large international operating organization, making it one of the least attractive players for Industry 4.0-implementation. Although this can be considered a good thing, if the implementation framework improves the margins over here, it will definitely improve it in the larger factories, it is also a burden in terms of resources and available knowledge regarding Industry 4.0. Resources like money and time were the foremost drivers which hampered full execution of the case study. Through the use of examples and by including perspectives, the case study still provided valuable information, and its intended purpose - showing how the model should look like - was fulfilled. However, actual implementation and its testing, still awaits.

Also, within this large organization incorporating multiple factories, it was valuable to observe how such a small factory could benefit significantly from a digital transformation. The factory of interest has, although its limited output, a key role in the supply of specialty fertilizers. In the near future, customers are likely to demand more customization and flexibility, thus increasing the market sizes of specialty products. As a result, the organization's view will shift slightly from bulk to specialty production to coope with the changing market needs. With this implementation model, the organization is able to quickly adapt to its new environment, without losing productivity due to the increasing complexity. This also clearly showed during the case study where the wide range of improvements on the various processes, indicated the immense applicability of this model.

Through the initial step, 'goal definition', it was clear that a direct connection with the strategic management was mandatory. In order to accurately obtain the global organization's needs an interview with the digital transformation director is required. Although many different internal reports and presentations provide a general feeling for the general objective, they do not describe it as accurate as the central team themselves do. Especially because the aim of this model is to redirect some of the central execution to a more local level, communication between the two is inevitable. This collaboration was not established at the very start of the case study, making it unnecessarily difficult to align to the global organization' intentions.

In the second stage 'business overview' it was key to describe a rather complex process by splitting it into multiple 'simple' ones. It was found that the 2D-RAMI model is particularly effective in describing the interconnected business processes and the associated communication channels and data transfer. Although this step was completely conducted in accordance with the separate departments, the availability of BPMN's (Flowcharts via Business Process Mapping) was exceptionally useful. If available, using these BPMN's to further construct the 2D-RAMI model is truly effective. However, it was found that some BPMN's do not describe the communication channels and the type of data very well, therefore requiring collaboration with the different departments as a bare minimum.

The consecutive stage of identifying the key variables is also considered to be a really successful one. The different data sets from the business overview provided a large list of data sets, i.e. variables, that are consistently used in the business processes. Through the participation in a quality team, each of these variables were assessed and together we concluded that five of them can harm the rest of the process considerably. However, due to nature of this set-up, i.e. a quality team, the results might differ from time to time. Subjectivity was limited by involving different people into the quality team and also by defining a relatively clear ranking system. Nonetheless, little bias in this selection procedure is inevitable and must be considered when analyzing the results. Having another team composition or performing this study at another moment in time (i.e. due to the ever changing nature of business processes) will infer different results.

Data collection, through both OT and IT merger and digital reporting, was probably the simplest stage of the case study. By clearly identifying the data and knowing where this data comes from (i.e. via the 2D-RAMI) enabled quick communication and transfer of said data. A positive attribute was the already large amount of data available, making actual OT-IT merger and digital reporting less relevant. Subsequently, the difficulties related to digital reporting and OT-IT merger were tested differently by retrieving historic information. OT and IT merger is considered as one of the major additions in Industry 4.0 as it allows manufacturers to reap the benefits of already existing and collected data. Since the company already had performed a similar approach recently, this step was analyzed and provided in this thesis to shed light on the critical aspects of it. The key elements of these two data collection stages are careful selection of what to measure (i.e. reduce chaos) and ensure that you measure what you want to measure (i.e. causality).

After the different data sets were collected, data analysis was performed. Similar to the description of section 5.2, the data analysis was just a free-flowing journey of trying different types of analysis to look for useful correlations and inconsistencies within the data. When said outlier was found, more attention was paid to the origin of it through further data investigation and by interviewing the responsible data owner. This unstructured data analysis approach allowed for deeper insight dedicated to specific needs of the particular data sets. For example, connecting the temperature data from a reactor vessel has nothing to do with the warehouse stocks of raw materials, therefore requiring a completely different analysis. However, due to the unstructured nature of data analysis, and due to immense knowledge base about the business processes that others might not possess, the results of the analysis heavily depend upon the one performing the analysis. Therefore, sequel research should pay attention to a more standardized way of doing data analysis.

Subsequently, the KPI selection stage relies on the output of the data analysis, and thus favors a structured way of doing analysis. However, the use of the SCOR model, and its KPI's, during the KPI selection stage was considered to be useful. Obtaining fruitful KPI's that can monitor the actual improvement of Industry 4.0 implementation.

The technology introduction stage was one which required the highest degree of creativity. Though Figure 2.5 provide a good overview of what and where to improve and implement, the overview only serves as a technology-portfolio without further depth about the actual vendors and type of technologies. To further enhance the practicability of this stage, Figure 2.5 should be upgraded with a vendor-portfolio. Within the company, such portfolio was already available, showing multiple vendors of different technologies that were already bound to the organization through contractual agreements. Other large corporations would benefit as well by creating an overview (i.e. portfolio) that contains available suppliers to support the local implementation teams.

At the end, the evaluation stage is one that might be skipped by some companies (mainly due to its predecessor's time path), but is fairly useful for future implementations. By assessing user satisfaction and the actual effectiveness the implemented technologies, the implementation team will gather valuable insights. Especially in the early stages of adoption, iteration of the implementation approach will happen continuously, therefore making the 'lessons-learned' the single most valuable support for future success.

The case study has shown that implementing the Industry 4.0-concept was straightforward. In just under a month we were able to pinpoint the critical aspects of the operations process by simply dividing into much smaller pieces. Also, the general understanding about the Industry 4.0-concept and its possibilities became much clearer by using the model. By carefully following the implementation models, companies could increase their adoption speed significantly as well as increase its adoption effectiveness through prioritizing the critical aspects. However, the model does not fulfil its full potential because some of the adoption barriers are still to be addressed (e.g.. cyber security and uncertainty about in- vs. outsourcing).

6 Conclusion & recommendations

This chapter involves the end of this research study by answering the research questions briefly. Following the conclusion on the research questions, and thus the elaboration of the model, come the recommendations for future research. The final comprises of a personal reflection in which I will assess the lessons learned throughout this intensive thesis project.

6.1. Conclusions

The main research question, which was more a design goal than an actual question, was subdivided into multiple sub-questions to clearly identify the separate topics to be covered in the thesis research. Through the design science model shown in section 1.4, each of these questions was addressed in the appropriate stage of the research, thereby aligning the created artefact (i.e. the implementation model) with the corresponding requirements (i.e. answers to sub-questions) belonging to the artifact.

Sub question 1: What steps exist in an implementation process and framework?
An initial answer to this question is formed by analyzing routine methods widely employed in the manufacturing industry. Six sigma turned out to the leading philosophy with regards to process improvements. One of these six sigma techniques; DMAIC focuses on problem solving by implementing new practices. Industry 4.0-adoption has - among many others - the goal of improving the existing processes by implementing new business opportunities. Therefore making these DMAIC process steps a perfect initial foundation for further construction of the detailed implementation steps.

In our analysis regarding Industry 4.0 we found that there are multiple ways to look at implementation processes. Current research stipulated the use of three major implementation categories encompassing the use of a certain degree of novelty in terms of technology: (I) using cloud technology and a few sensors to enhance existing data flow, (II) Automated processes and advanced analytics, and (III) Smart manufacturing with full scale flexibility. All three categories allow us to define the stage of novelty for companies that already implemented some Industry 4.0-related technologies. Moreover, it aids organizations to define the future plans in what to consider in the next implementation stage. However, these implementation stages do not infer what actions must be made prior to a successful implementation. For this, we had to review other research dedicated to implementation practices.

Since the aforementioned adoption stages do describe actual implementation, we defined the actual implementation stages in subsection 2.3.2. Using an existing model by Aitken *et al.* (2004) and aligning it with common practice within the industry, a new set of implementation stages was created that fit into the DMAIC model of the Six Sigma-philosophy. ***The final, inclusive, answer to the sub-question comprises the following 8 implementation steps:***

1. Set the goal definition;
2. Create a business overview;
3. Identify key variables;
4. Gather data through: (I) OT-IT merger, and (II) Digital reporting;

5. Perform data analysis;
6. Specify KPI's;
7. Introduce technology;
8. Monitor continuously;
9. Improve;
10. Evaluate.

Sub question 2: How are the key characteristics of a supply & planning environment that are required to construct and Industry 4.0-architecture found?
At the very start of this research thesis it was perceived that industry 4.0-related technologies are introduced on a basic set of pre-determined parameters, like budgets, constraints, and minimum requirements. This perception was based upon a preliminary study which only focused on understanding the ambiguous concept 'Industry 4.0'. Although it was found that these pre-determined parameters are not used as such, their application became immensely valuable when developing the implementation model. At the point of selecting key variables, data analysis, and selecting KPI's, knowledge about how the different supply & planning characteristics are interconnected was the major source of information. Therefore making the second research question relevant again, but with a different intended use.

As a result, the answer slightly differs from the question asked, yet significantly contributing to the progression of the implementation model, i.e. main research question. The answer to the second sub question is twofold; where one is similar for each implementation and the other is context-dependent. ***For every implementation, regardless of the context, holds that KPI's are easily derived from the SCOR approach.*** These standardized performance indicators shed light on the efficiency of the different processes from multiple angles. By applying benchmarks on each of these pre-determined KPI's it becomes possible to compare results with the competition to see how well the company performs and how well it should perform.

Prior to the KPI selection is the key variable selection, which encompasses the context-depended draft. Through the creation of the business overview a list of commonly used variables (i.e. characteristics) is obtained. After careful elimination, only the key characteristics, applicable to that particular supply & planning environment remains.

Sub question 3: What are the available Industry 4.0 technologies that aid supply & planning departments?
Various views on the technologies-side of Industry 4.0 have been considered and investigated. Due to the concept being so vague, Industry 4.0 includes many different streams and practices, all involving different technologies and different terminology. Terms like Cyber Physical Systems (CPS) and Internet of Things (IoT) were used interchangeably in one paper, while they were mentioned contradictory in another. By answering this sub-question, and keeping its intended purpose in mind (i.e. implementation model), a set of 13 distinctive technologies were identified.

These 13 technologies can all be deployed in the supply & planning environment considered, described in subsection 2.1.1. Although some of them still overlap; e.g. Miniaturization of electronics and IoT, their enabling nature is completely different, i.e. allowing small sensors and interconnected sensor systems. ***A more practical approach was taken in Figure 3.4, where practically applicable technologies were taken on the basis of the 13 enabling technologies:***

1. Virtual and augmented reality;
2. Additive manufacturing (3D);
3. Miniaturization of electronics;
4. Robotics, drones and nano-technology;
5. Blockchain;
6. Simulation;
7. Big Data analytics;
8. Automatic Identification and Data Collection (AIDC);
9. Machine to Machine communication (M2M);
10. Cloud technology;

11. Cyber security;
12. Business intelligence;
13. Internet of Things (IoT).

Sub question 4: What must be incorporated to develop a sustaining process that fits into the company's culture?
The final sub question was one that was supposed to evolve from the case study research. By going through the model once, it should be observed what kind of implications one would run into and subsequently what kind of countermeasures should be taken. However, the answer to this question developed quite early, as many of the case studies and practitioners mentioned several implications and challenges faced during their implementation process. The expression says 'do not reinvent the wheel', which also holds true for the pitfalls that someone else already experienced, and learned from.

Therefore, we were able to learn from the challenges faced and adjusted the model accordingly. As was discussed in chapter 5, not all of the challenges were solvable yet, however, multiple of them were. The solutions that this implementation model offers to maintain a sustainable and useful process, which is adapted to a company's culture are the following:

- **People management:** One of the most critical issues regarding Industry 4.0-adoption is the user adoption and satisfaction. ***Through the implementation stage of the model, training and user feedback are included, thereby decreasing the change of a misfit between users and technology.*** Moreover, the evaluation step dedicates its efforts to reviewing user satisfaction to generate feedback on the implemented systems;
- **No standardized option for all factories:** A lot of organizations see standardization as a key element for improving efficiency. However, standardized products are often a misfit with the majority of the users, reducing its effectiveness significantly. ***To remain effectiveness and increase efficiency, the standardization is found in the implementation model, and no longer in the technology, allowing all factories to perform digital transformation in an unambiguously manner***;
- **Determine the right business needs:** For several practitioners it was considered the most difficult task of the implementation process. Due to its context-dependent nature, a structured approach of finding the right spot for implementation was necessary. ***By means of a 2D-RAMI model and a subsequent stage of identifying the key variables, this structured approach was made.***

Main question: How can Industry 4.0 be implemented into supply and planning departments of complex manufacturing companies using an implementation framework?
The answer to the main element of this thesis; constructing the implementation framework, is the combination of all aforementioned answers and is captured all in one large figure; Figure 3.1. Through a set of incremental implementation stages, all incorporating different actions, digital transformation in a supply & planning environment of a complex factory is realized.

6.2. Recommendations & future work

The incentive for this thesis research was to clarify and simplify the introduction of Industry 4.0 into complex factories. To delineate the broad concept of Industry 4.0, the focus was directed towards raw material supply & planning, incorporating all important business processes for the operations of a manufacturing company. Although the goal of the thesis is reached; providing an useful and effective implementation model for complex factories, the research is not finished and is still open for future research. chapter 5 elaborated upon the limitations of this study, and this section will subsequently derive the research yet to be covered. The substantial recommendations for future research are the following:

- **Defining clearer deliverables:** As was indicated in the discussions, there are no clear boundaries between some of the implementation stages. Because the level of detail is not apparent in the actual model, only the case study is providing some sort of delineation on what is expected at each stage. In future iterations of this model, such boundaries must be much clearer to grant the user of the model a better idea on what is expected and how much time is required;

- **General technology portfolio:** This research made significant efforts in clarifying and specifying the broad landscape of different technologies. By visualizing them into a RAMI architecture, the applicability and objective of each technology becomes more apparent. However, in future work, more attention is required on further clarifying all available options through some sort of technology portfolio;
- **Data analysis:** Data analysis was the most fuzzy and unclear stage of the process. Because of previous experience in data analysis and by knowing the businesses processes on a very detailed level, the execution of this stage was relatively simple. However, for other practitioners this might become a major burden because of the unstructured nature. Therefore, more attention should be paid to descriptive data analytics and data statistics to provide a structured data analysis approach;
- **Effectiveness:** Due to the lack of similar implementation models and due to the limited output of the case study, the model's effectiveness was measured poorly. Currently, the effectiveness is the perceived utility by internal stakeholders. In future studies this utility must be examined by external practitioners to increase the study's rigor;
- **Generalizability:** The final recommendation focuses on the applicability of the implementation model on other factories. The model was tested only once, on a complex factory in the agriculture fertilizer industry mainly producing solid fertilizers. Production of solid fertilizers involve the storage of raw materials in warehouses rather than in storage tanks, which is the case for liquid raw materials. Such difference can have a significant impact on the application of the model due to the importance of completely different key variables. Also, the model should be applicable to markets other than agriculture fertilizers, requiring more case studies in different markets to verify its generalizability.

Not only the academic world would prosper from future work and recommendations, but the environment of the performed case study would as well. Throughout the case study a wide variety of topics have been touched upon, one more useful than the other. As a result, we developed a deep understanding about the operations process within the company connected to the Industry 4.0-implementation. To enhance future progression and existing operations performance the following activities are recommended:

- **General technology portfolio:** Similar to that of the academic recommendations, is the development of a general technology portfolio. Within the global organization a catalogue of digital solutions was available. However, this catalogue included only digital opportunities (i.e. software), but still lacks solutions like physical things (e.g. RFID), digitization (e.g. ZigBee), and communication (e.g. Edge) which have significant benefits as well. Enhancing the existing portfolio/catalogue with these technologies allows local units to quickly find the best possible solution and grants the central unit to procure these technologies at larger scale thus lowering the price;
- **Actual technology implementation:** During the case study it was not possible to actually implement some of the new Industry 4.0-technologies due to the lack of resources. Utilizing this model supports the generation of clear and viable business cases, which on their turn can release investment at the central organization to start actual implementation;
- **Perform a second implementation loop:** This first implementation loop already included a lot of useful insights and helped to reduce the complexity of intertwined business processes. By doing this again, now including new stakeholders from the different departments, would increase the general understanding of the interdependencies. Moreover, addressing new variables and finding appropriate technology solutions will increase the company's competitive advantage;
- **RAMI utilization:** One major goal of the RAMI-model is providing a basic framework with which companies can model the internal architecture of the different technologies operating together. The implementation framework of this model did not emphasize the use of RAMI beyond the 2D-version of it. Yet the use of its original form can certainly be beneficial to show how the different technologies are connected to one another and how these connect to the rest of the company;

- **Start data sharing:** The simplest, yet the most crucial, recommendation is related to internal data sharing. Many departments hold their data for themselves, simply because they do not see the value of data sharing. However, in many cases knowing that the data exists and being able to access it, would already reduce the amount of incorrect actions.

6.3. Reflection

During the past period of 6 months this thesis research was conducted in partial fulfilment of the masters degree of Management of Technology (MoT). Through this lengthy period, a lot of different challenges crossed my road that contributed to my personal development. The most prominent challenge was the emerge of the COVID-19 pandemic, which both eliminated face-to-face contact and forbid traveling to the TU Delft and the company. This major burden resulted in the delay of many tasks, like interviewing and retrieving data, which required the fast development of a new skill; flexibility. Due to the time being limited, and the high dependence on input of others, particular actions had to be postponed, while others had to be accelerated.

Another trait that evolved under the scope of this research is the ability to effectively connect different constructs. Especially the development of the 2D-RAMI model and its connection with the key variable-selection is seen as an useful and novel addition. Moreover, the use of the quality improvement model within DMAIC clearly helps practitioners to understand the implementation process.

Contrary to the improved characteristics are the habits that still need attention in the future. One of the major concerns during this thesis was found in procrastination. Especially the writing of the thesis was taken to the last moment, which can infer issues in the future. Also, the size of tasks undertaken can overwhelm me over time. At the very start of this thesis, I had a concise plan in what to include and how to shape the thesis over time. Eventually, this plan was considered to be too ambitious and items like the technology-portfolio were abandoned for future research.

Not only did I learn how to implement technologies in an effective manner, I also developed a deeper understanding about the effectiveness and applicability of the several technologies within the supply & planning domain of complex factories. Some of the technologies suit the supply & planning environment much better than others. Therefore I will describe my view about the usefulness of three top categories of technologies in complex factories using the information and knowledge gained.

Especially the use of Internet of Things and the different options of Automatic Identification and Data Collection (AIDC) were found to be important. The old-fashioned factories use quite some software like SAP and databases to store their information and to retrieve it in an easy manner. However, it is the collection and storing of data that still requires a lot of attention. Small fluctuations, for instance with picking the wrong material from the warehouse, can happen quite frequently. These small changes diminish the accuracy of the data stored inside the databases and software, thereby reducing the effectiveness. To cut out the middleman, you should use methodologies like RFID, bar codes or IoT sensor networks to simply feed the databases and software with the data required. Although the use of bar codes is already dated, its implementation is much more easy compared to RFID tags. If a multitude of your suppliers already applied RFID tags to their products (i.e. for their own convenience), adoption of RFID tags becomes straightforward and offers more possibilities compared to bar codes.

Increasing the use of sensor networks simultaneously increases the required bandwidth and connectivity in and around the factory. As a result, the use of Edge systems (i.e. processing power on site) and installing various routers is a must-have. That makes enabling technologies like miniaturization of electronics, but also cyber security, more important. These technologies determine the limitations of an Industry 4.0-environment and require careful examination as soon as the adoption of IoT and AIDC increases.

The third category of useful technologies is found in software and storage. Many companies already switched to cloud services, Microsoft Office 365, and utilize data analytical- or simulation-related software. These technologies can already handle a good amount of data and were likely a capital-intensive investment. This makes the introduction of these technologies a lower priority until the limitations of said technologies have been reached. An additional benefit of this 'delay' in improvement is the increase in available data. Current software is based upon a minimal amount of data and only uses a part of the new incoming 'big' data flow of the IoT and AIDC systems. By the time new software is required, the significant inflow of data allows for more and sophisticated functionalities.

A final note is dedicated to the Business Intelligence and machine learning/artificial intelligence form of Industry 4.0. The increase in incoming data also allows to redirect the majority of decision-making towards processing units rather than humans. In the functions-layer of the 2D-RAMI model we already shown how some decisions are made. By knowing exactly what boundaries apply and how the data is interpreted, we can define an algorithm that can do this itself.

A

Design science

Now we know the current status of Industry 4.0, we have to identify ways to design the model. In the past, scientists focused on the way of information system research being conducted in order to improve the research process. Throughout this process, Nunamaker *et al.* (1991) identified 5 different ways of research, each of them having a different purpose. The list by Nunamaker *et al.* (1991) comprises (1) basic and applied research, (2) scientific and engineering research, (3) evaluative and developmental research, (4) research and development, and (5) formulative and verificational research.

In order to structure all different streams of research, Nunamaker *et al.* (1991) develops a research methodology that involves processes, methods and tools which can be applied to each of the basic research categories. Such model further improves the effectiveness of research by incorporating every important aspect necessary. This comes in very useful for developmental research, as this is often lacking vigor, because of the uncertainty of completeness. Since this study focuses on the development of a framework, research methodologies that enhance the credibility by applying structure are really useful.

The basis of the methodology by Nunamaker *et al.* (1991) consists of 4 building blocks: theory building, experimentation, observation and system development. All steps are intertwined and can evolve throughout the research process. Theory building targets conceptual frameworks, mathematical models, and methods. Experimentation comprises all experiments, laboratory or field, and simulations that have as sole purpose to test different hypotheses. The observation, on its turn, aims to understand the theory by doing case, survey, or field studies. Finally comes the system development which involves prototyping, product development and technology transfer.

Nunamaker *et al.* (1991) captures these four essential building blocks in their systems development research process:

1. *Construct a conceptual framework*, i.e. produce a meaningful research question and understand the context of the issue;
2. *Develop a system architecture*, i.e. define system components, their interrelationships and modularity;
3. *Analyze & design the system*;
4. *Build the (prototype) system*;
5. *Observe & evaluate the system.*

Though the model by Nunamaker *et al.* (1991) focuses on the design of a model, their approach is rather theoretical (Peffers *et al.*, 2008). Since this study targets a practical and theoretical dilemma, the applicability of the multimethodological system by Nunamaker *et al.* (1991) becomes obsolete. To cover both theoretical and practical information strategies, Peffers *et al.* (2008) proposes the Design Science Research Methodology (DSRM). The goal of their DSRM is "to help researchers with presenting research having a commonly understood framework, rather than justifying the research paradigm on an ad hoc basis" (Peffers *et al.*, 2008). This model, mainly differs in the separation of the first step the process by Nunamaker *et al.* (1991) into problem identification and solution objectives. This clear distinction enables researchers to approach the problem both practically, like feasibility, and theoretically, the underlying explanation. The full DSRM model is shown in Figure A.1.

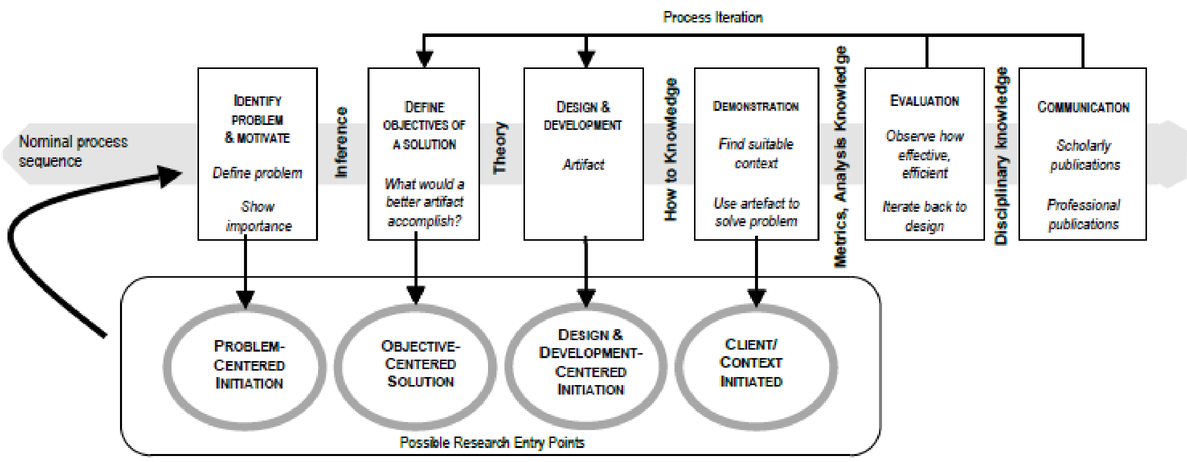

Figure A.1: The Design Science Research Methodology (DSRM) proposed by Peffers *et al.* (2008).

In order to streamline the research process and the design of the implementation framework during this study, the DSRM model is taken as basis. The identification of the problem and the motivation of it, is part of this kick-off proposal. Also the objectives of the solution is shortly touched upon through this proposal, which is part of the conceptual design. Further design, demonstration, evaluation and communication are topics of the final thesis.

B

Literature study

In order to gain the right information and to develop a research based on useful performed studies, the need for proper search and selection criteria is high. Throughout the exploration of helpful material, it was recorded what kind of search was done. This literature study obtained information via 4 different literature review strategies that developed on top of each other.

1. Initial search for known topics, such as ”Smart factory” and ”Industry 4.0”. These topics were directly inserted into regular search engines; e.g. Google Scholar and Sciencedirect. The focus of this strategy lies within the ’exploratory’, discarding any literature concentrating on specific technologies, algorithms or anything other than the interest of this review.

2. From these initial documents a significant amount of similar, yet more specific, definitions were found, like ”Internet of things”, ”intelligent ...” and ”Computer-aided Manufacturing (CAM)”. Increased with the AND-function and words as ”factory” and ”industry”, these definitions were used to further narrow the focus and the amount of available documents. Mainly ”factory” seemed to be an important term, due to the widespread application of internet of things.

3. After scrolling briefly through a part of the large amount of sources a more refined search term was introduced, coupling the two different fields of interest, smart factory and raw material planning. Because there are a lot of areas in which raw material planning takes place, it was chosen to identify this space with words like ”logistics” and ”process planning”. At this stage, only the more sophisticated search engine, Scopus was used.

4. In the final stage some documents were found that mentioned production resource planning, which tightly describes the aim and purpose of this literature review. Such search terms were also specifically used, however, without any luck. It appeared to be a dead end.

These four strategies provided a multitude of literature material that enables insights on many fronts; from a managerial perspective to a step-by-step approach for a legion of metrics (Columbus, 2019). Each strategy was further fine-tuned or broadened to facilitate full exploration in the used search engines. The development of the first two exploratory strategies is presented in Table B.1. These are articles which have not been fully read, but provide a solid basis of information if necessary in the future research regarding specifically smart factory.

During application of the first two strategies, it was found that some search descriptions were too broad and gave room to too many articles, that only the most relevant ones were withdrawn. Relevance was determined on three attributes; whether the article indeed described a manufacturing environment, whether the article was recently published (i.e. articles originating from 2007 were the first to define strategies and topics relevant for Industry 4.0 (Saucedo-Martínez *et al.*, 2018; Osterrieder *et al.*, 2019), everything before is considered to be part of Industry 3.0, with advanced Progamming Logic Controllers (PLC) that are already widespread in the manufacturing industry), and if the article added new information on top of the traditional manufacturing. A significant amount of articles have

Strategy	Engine	Term(s)	Useful hits*	Remarks
1	Google Scholar	Smart factory	13	Lot of irrelevant articles
1.1	Google Scholar	Smart factory/Industry 4.0 AND review	8	
1	Sciencedirect	Smart factory	-	Too broad - no good hits
1.1	Sciencedirect	Smart factory AND review/analysis	1	Leads to repetitive results
2	Google Scholar	Factory/industry AND IoT/CAM/intell.	6	CAM was irrelevant
2	Sciencedirect	Factory/industry AND IoT/CAM/intell.	2	IIoT introduced
2.1	Sciencedirect	IIoT	3	
2.2	Scopus	SF/I4.0 AND implem/side-ef/etc.	3	
2.2	Sciencedirect	SF/I4.0 AND implem/side-ef/etc.	2	

Table B.1: Search and description development (*) only retrievable ('TU Delft free') articles were considered, doubles were disregarded as well.

been discarded, due to the broad search. However, this exploratory search generated interesting examination strategies.

Initial relevant terms turned out to be obsolete due to their insignificant correlation to the subject of this review, like Computer-aided manufacturing (CAM). Moreover, a new search term, IIoT, was introduced and enabled the find of multiple articles. The terms as shown in Table B.1 provide the current obtained articles, but are not limited to future finds.

After finishing the exploring stage about smart factories, it was chosen to develop further on the combination of the two topics, i.e. strategies 3-4. The results of these strategies are in chronological order shown in Table B.2. All the hits were found in Scopus in the "Article title, Abstract, Keywords"-area.

Terminology	Hits
smart AND factory AND internet AND things AND supply AND chain	40
smart AND factory AND internet AND things AND logistics AND raw AND Material AND planning	0
smart AND factory AND internet AND things AND raw AND Material AND planning	1
smart AND factory AND internet AND things AND logistics AND planning	**4**
factory OR industry AND "internet of things" OR IoT AND Logistics OR "Smart logistics"	342
factory OR industry AND "internet of things" OR IoT AND logistics OR "Smart logistics" AND planning	99
factory OR industry AND "internet of things" OR IoT AND supply AND planning	52
factory OR industry AND "internet of things" OR IoT AND supply AND planning AND warehouse	**7**
factory OR industry AND "internet of things" OR IoT AND "production resources planning"	**1**
*F OR I AND "IoT" OR IoT AND "enterprise resources planning" OR "ERP"	74
*F OR I AND "IoT" OR IoT AND "enterprise resources planning" OR "ERP" AND "production process"	**5**

Table B.2: Search and description development in a more dedicated search area. All bold numbers are the articles used for further development. (*) the last two rows wield the same first 4 terms as rows 5 to 9, but for the sake of lay-out, these have been abbreviated to the first character.

As shown in Table B.2, strategy 4 was used twice. During the full reading session, it was found that Enterprise Resource Planning (ERP) was a widely used term to refer to the planning systems of a factory. In order to capture these specific, and likely useful, articles an extra search term was introduced "Enterprise resources planning". This term revealed many irrelevant articles that described the particular handling of IT models, which is yet too specific. For this reason, the majority was cut out by applying the term "production process", which enabled the articles that connect production and planning to smart factory/Industry 4.0.

All reviewed articles have been read thoroughly and specified into several subcategories as shown in Table B.3. First of all, it was of significant value to define whether the paper was having a broad or focused approach. The main characteristic for a broad paper would be the explanation of various topics, including a well-defined search strategy. Focused articles, on the other hand, mentioned specific cases and dived into one of the main characteristics within Smart factory research.

After the approach was defined, the specification, aim and data were determined. For the specification it was important to distinguish between a practical and theoretical article, as this will help to construct future arguments that require either practical or theoretical approaches. The aim of the article was captured within: Verification, Exploratory and Explanation. Such terms only indicate the state of the research. The lack of verification articles can be described by the early stage of research we are in Mittal *et al.* (2019). Finally, the data used was defined by either: Literature, Case study, Interviews and Surveys. Again, the lack of interviews is likely to be caused by the current stage of research, as only few experts exist within the Smart Factory landscape.

In the final stage, it was specified in which research pillar, opted in Osterrieder *et al.* (2019), a particular paper was placed. Also the relevance (i.e. importance) of each article was decided. When an article was considered to be not relevant at all, e.g. score 0, it was left out of Table B.3.

#	Reference	Approach		Spec [x]		Aim			Data				Focus (topic)	Imp[y]	Future research	Remarks
		F[1]	B[2]	P[3]	T[4]	V[5]	E[6]	Ex[7]	L[8]	C[9]	I[10]	S[11]	Research pillar[z]	(1-10)		
1	Osterrieder *et al.* (2019)		X		X		X		X				8	7	-	
2	Zheng *et al.* (2019)	X		X				X		X			3	2	Verification	
3	Belli *et al.* (2019)	X		X				X		X			5, 6	9	Generalizability	
4	Do Chung *et al.* (2018)	X		X				X		X			3	4	-	Only theory was used
5	Lee *et al.* (2017)	X		X				X		X			2, 4	9	Generalizability	
6	Wang *et al.* (2016a)		X		X		X		X	X			8	7	Verification	
7	Saucedo-Martínez *et al.* (2018)		X		X		X		X				8	6	-	
8	Accorsi *et al.* (2018)	X		X	X		X	X	X	X			3, 4	3	Generalizability	Focused into one company
9	Manavalan and Jayakrishna (2019)		X		X		X		X				3, 5	4	Green SCM	
10	Trstenjak and Cosic (2017)		X	X				X	X				1, 3	4	Product relevance	Some intersting topics
11	Tjahjono *et al.* (2017)		X		X		X					X	3	5	Which KPI's	
12	Karabegovic *et al.* (2020)		X		X			X	X				8	4	-	
13	Kumar *et al.* (2019)	X			X			X	X				8	4	-	
14	Douaioui *et al.* (2018)	X			X		X		X				8	2	-	Irrelevant
15	Chaopaisarn and Woschank (2019)	X	X		X		X		X				8	8	Emperical research	Focus on SME's
16	Yang *et al.* (2019)	X		X	X		X	X		X			8	10	Plug and play	
17	Xu and Hua (2017)	X		X				X		X			1	5	Verification	
18	Arnold and Voigt (2019)	X			X		X					X	8	2	Other factors	Gives additional insights
19	Chong *et al.* (2018)	X		X				X		X			5, 6	1	Integration	Far too focused
20	Arumugam *et al.* (2018)	X		X				X		X			3	2	Scale-up	
21	Lee (2019)	X		X				X		X			2, 3	2	Generalizability	
22	Chen *et al.* (2017)	X		X		X		X		X			2, 3	3	Generalizability	Step-by-step approach
23	Mittal *et al.* (2019)		X		X		X		X				8	8	Verification	
24	Reaidy *et al.* (2015)	X		X				X		X			7	3	Generizability	
25	Rezaei *et al.* (2017)		X		X			X		X			3, 8	7	Evaluation	SSCM on a broad level
26	Frank *et al.* (2019)		X		X		X		X				8	7	-	
27	Moktadir *et al.* (2018)	X		X			X				X		4	5	Verification	
28	Crnjac *et al.* (2017)		X	X	X			X	X				3	4	Environment	Business models
29	Oztemel and Gursev (2020)		X		X		X		X				8	9	Practicability	
30	SMLC (2011)		X	X				X			X		-	4	-	Industry-wide challenges
31	Wang *et al.* (2016b)	X		X				X		X			5	4	Optimization	

Table B.3: All reviewed articles that were considered to be somehow relevant during the literature study. In order to align the table accordingly several abbreviations were made: [1] Focused, [2] Broad, [3] Practical, [4] Theoretical, [5] Verification, [6] Exploratory, [7] Explanation, [8] Literature, [9] Case study, [10] Interviews, [11] Survey, [x] Specification, [y] Importance with regards to the topic of this review. And finally [z], the research pillars by Osterrieder *et al.* (2019): 1. AI manufacturing, 2. Data handling, 3. Supply Chain Management, 4. Decision making, 5. IoT, 6. Digital transformation, 7. IT Infrastructure and 8. Theoretical contributions.

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