Enterprise Architecture for Digital Manufacturing

EA models and an automated EA modelling method to support Industry 4.0 transformation

Nardello, Marco

ENTERPRISE ARCHITECTURE FOR DIGITAL MANUFACTURING

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BY
MARCO NARDELLO

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AALBORG UNIVERSITY
DENMARK

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CV

Marco Nardello was born on the 24th of March 1991 in Varese, Italy. He completed a BSc degree in IT security at the University of Milan in 2012. In 2014, he completed an MSc in Software Development with a specialization in enterprise architecture at the IT University of Copenhagen. He subsequently joined the IT strategy division of Deloitte Consulting Italy and worked on enterprise architecture and IT architecture projects in the financial sector until October 2016. Shortly thereafter, he started his PhD at the Department of Materials and Production of Aalborg University. His research on enterprise architecture for digital manufacturing is part of the Manufacturing Academy Denmark (MADE) project, which is funded by the Innovation Fund Denmark.

ENGLISH SUMMARY

Technological progress has allowed enterprises to collect large amounts of data on their products, processes, and services. This progress is part of the Industry 4.0 transformation. Due to this transformation, enterprises are likely to become better at using data to improve their products, processes, and services. However, to do so, enterprises need to redesign the ways in which they collect, structure, analyse, and share data, including the sharing of data across departments and with other enterprises. Transforming an enterprise and its processes in such a manner that data can be leveraged to improve processes, products, and services is challenging. Such a transformation requires that departments understand the processes of other departments and share relevant data.

Enterprise architecture (EA) is a discipline that focuses on managing transformations involving an entire enterprise. It aims to effectively implement enterprise strategies by designing the way departments work to maximize coherency between departments. To implement an enterprise strategy, EA models an enterprise's current goals, processes, applications, and infrastructure and identifies the desired ones. Current EA models provide the starting point for redesigning enterprises to leverage data for improvement. However, there are two main challenges in using EA models in manufacturing. First, they are seldom used for modelling manufacturing products, processes, and resources. Second, EA models are usually created manually, which is inefficient, time-consuming, and error-prone.

To redesign an enterprise in such a manner that it can leverage data, EA needs to overcome these challenges. This thesis sets out to develop EA models intended to support manufacturing to allow data to be used to automate the creation of EA models. These models leverage data from several systems to make information more accessible within an enterprise and support it in using data to improve its processes, product, and services. Building on six articles, this thesis contributes to achieving the following three objectives:

1. *Exploring the use of EA models for manufacturing.* Through the application of new standards related to Industry 4.0, EA models intended to model manufacturing products, processes, and resources are developed.
2. *Leveraging data to create EA models for manufacturing*. By improving on the few existing automated modelling methods, a new automated modelling method is developed for creating EA models based on data from manufacturing execution systems and enterprise resource planning systems.
3. *Leveraging data to enhance EA models for manufacturing.* Building upon the method developed for the previous objective, additional data and information (e.g. performance measurements from production lines and assembly documentation) are included in the automatically created EA

models. As a result, the models can assist in monitoring the performance of manufacturing processes and thus facilitate their improvement.

These EA models and method were first tested at the Industry 4.0 learning factory at Aalborg University and thereafter among a number of participating manufacturing companies. Among the participating companies, the research conducted for this thesis was undertaken in particularly close collaboration with QualiWare ApS, an EA vendor, and several manufacturing companies.

This thesis serves as a point of departure for researchers that aim to contribute to EA to support the Industry 4.0 transformation. The EA models and method presented in this thesis can be further applied and developed to better model manufacturing products, processes, and resources. In addition, the method presented in this thesis significantly improves the creation of EA models by leveraging data to overcome the challenge associated with manually developing such models. This thesis can also provide guidance for production managers who wish to improve the use of manufacturing data in their enterprises through employing EA models.

DANSK RESUME

Den teknologisk udvikling giver virksomheder mulighed for at indsamle en stor mængde data omkring deres produkter, processer og services. Denne udvikling er en del af Industri 4.0-transformationen. Med denne transformation vil virksomheder være bedre i stand til at bruge data til at forbedre deres produkter, processer og services. Men for at være i stand til at anvende data er virksomhederne nødt til at redesigne den måde de indsamler, strukturer, analyserer og deler data på. Dette kræver at data deles imellem afdelinger og virksomheder. Det er udfordrende at omdanne en virksomhed og dens processer nytte data til at foretage forbedringer af processer, produkt og services. Det kræver, at en således at den kan forstår de processer som foregår i andre afdelinger og deler relevant data med hinanden.

Enterprise architecture (EA) er en disciplin som kan styre transformationer, der involverer hele virksomheden, og som sigter mod at implementere virksomhedsstrategier effektivt ved at designe den måde, afdelingerne arbejder sammen på. For at implementere en virksomhedsstrategi modellerer man i EA de "aktuelle" virksomhedsmål, processer, applikationer og infrastruktur og designer de fremtidige mål. Aktuelle EA-modeller er udgangspunktet for at redesigne virksomheder til at udnytte data til forbedring. Der er dog to hovedudfordringer ved brug af EA-modeller inden for produktion. For det første bruges de sjældent til modellering af produkter, processer og ressourcer. For det andet genereres EA-modeller normalt manuelt, hvilket er ineffektivt, tidskrævende og det kan kan medføre fejl.

For at redesigne en virksomhed til at udnytte data skal EA overvinde disse udfordringer. Denne afhandling undersøger, hvordan EA kan understøtte redesign af produktion afdeling til bedre at udnytte data til forbedringer. Formålet er at udforske udviklingen af enterprise architecture modeller til produktion og omdanne udviklingen af enterprise architecture modeller til at udnytte data. Baseret på seks artikler bidrager denne afhandling til att opnå følgende tre mål:

1. *Undersøge brugen af EA-modeller* til produktion afdeling ved at identificere EA-modeller, der er egnede til fremstilling af produkter, processer og ressourcer.
2. *Udnytte data til at oprette EA-modeller* til produktion afdeling ved at udvikle en ny automatiseret metode til oprettelse af enterprise architecture modeller baseret på data fra produktionssystemer og ressourceplanlægningssystemer.
3. *Udnytte data til at forbedre EA-modeller* til produktion afdeling ved at inkludere yderligere data i enterprise architecture modellen på baggrund af den nye metode med det formål at overvåge prestationen af produkter, processer og ressourcer i producktionen.

Disse EA-modeller og -metoder er først demonstreret i Aalborg Universitets Industry 4.0 learning factory og dernæst testet på flere produktionsvirksomheder.

Afhandlingen henvender sig til forskere inden for EA og Industri 4.0. De EA-modeller og metode, der er præsenteret i denne afhandling, kan yderligere anvendes og udvikles til at forbedre modellingen af produkter, processer og ressourcer. Derudover forbedrer metoden markant oprettelsen af enterprise architecture modeller ved at udnytte data til at overvinde udfordringene ved manuelt at udvikle enterprise architecture modeller. Denne afhandling kan desuden udgøre et springbræt for produktionsledere til at øge brugen af produktionsdata i virksomheden gennem brug af EA-modeller.

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Marco Nardello
Aalborg, November 2019

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Article 3. Nardello, Marco, Charles Møller, and John Gøtze. 2017. "Organizational Learning Supported by Reference Architecture Models: Industry 4.0 Laboratory Study." *Complex Systems Informatics and Modeling Quarterly*, no. 12: 22–38.

Article 4. Nardello, Marco, Charles Møller, and John Gøtze. 2018. "Process Model Automation For Industry 4.0: Challenges For Automated Model Generation Based On Laboratory Experiments." *CEUR Workshop Proceedings* 2218: 201–16.

Article 5. Nardello, Marco, Shengnan Han, Charles Møller, and John Gøtze. 2019. "Automated Modeling with Abstraction for Enterprise Architecture (AMA4EA): Business Process Model Automation in an Industry 4.0." *Complex Systems Informatics and Modeling Quarterly*, no. 19.

Article 6. Nardello, Marco, Shengnan Han, Charles Møller, and John Gøtze. 2019. "Incorporating Process and Data Heterogeneity in Enterprise Architecture: Extended AMA4EA in an International Manufacturing Company." In the 3rd round of review at *Computers in Industry*.

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CHAPTER 1. INTRODUCTION

This chapter introduces the main concepts explored in this thesis, as well as its industrial motivation and objectives. The first two sections guide the reader by presenting the Industry 4.0 transformation at the industry, enterprise, and functional unit levels. These sections outline the requirements for the Industry 4.0 transformation of an enterprise and illustrate them with examples. Furthermore, the practice problems that motivated the research presented in this thesis are identified. Thereafter, Section 3 introduces enterprise architecture (EA) discipline, while Section 4 presents this thesis' objectives. These sections also outline the role played by EA in addressing these problems. The final section describes the structure of this thesis.

The manufacturing industry is of great importance to modern society and is constantly evolving. In 2019, the manufacturing industry employed around 14% of the world's workforce.[1] Furthermore, the manufacturing industry deeply shapes people's everyday lives by providing them with products such as furniture, clothing, and technological devices. Sustainability, the internet of things (IoT), and predictive maintenance are some of the leading trends in the manufacturing industry and are having a profound impact upon it. Manufacturers are becoming increasingly connected with their customers through the IoT and smart products, while supply chains are becoming more integrated and companies more connected. Manufacturing is moving towards connected products and the integration of engineering across the entire value chain. Factories and production sites are becoming increasingly connected and processes more integrated. An empowered workforce is crucial to the Industry 4.0 transformation, and employees are becoming increasingly connected through smart equipment. The abovementioned developments are the beginning of what is commonly referred to as the fourth industrial revolution, which, in the remainder of this thesis, is referred to as the Industry 4.0 transformation.

1.1. SMART PRODUCTS AND DIGITAL ENTERPRISES

To better understand the changes occurring in the manufacturing industry, it is important to understand the transformation of products and enterprises.

Consider the example of a car, the most popular mode of transport in developed countries. A conventional car communicates information concerning performance that

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[1] https://www.ilo.org/ilostat/faces/oracle/webcenter/portalapp/pagehierarchy/Page3.jspx

it may be experiencing to the driver but cannot share them directly with the manufacturer of that vehicle. A manufacturer may eventually assess the condition of a car when it is serviced without knowing how it has been used, its performance, and where and in which environmental conditions it has been driven. When it comes to servicing cars, most manufacturers require them to be serviced at predetermined times or after certain distances, but a manufacturer cannot know whether a vehicle actually needs to be serviced. In the event of a manufacturing flaw, conventional cars have to be recalled to fix the issue. In 2009 and 2010, Toyota had to recall 9 million vehicles due to a pedal issue, and during the same years Ford recalled 14.9 million vehicles to fix a cruise control issue.[2] In 2015, Toyota recalled 6.5 million vehicles due to faulty power window switches.[2] In the same year, Volkswagen recalled more than 4.5 million cars when it was revealed that the manufacturer had used software to conceal its vehicles' emissions.[2] Such issues endanger both people’s lives and the survival of car manufacturers.

The Industry 4.0 transformation is leading to improvements in the capabilities and value of products (Porter and Heppelmann 2014, 67). Smart products consist of three types of components (Porter and Heppelmann 2014, 67): Physical components are the mechanical and electrical parts of a product (Porter and Heppelmann 2014, 67). Smart components include sensors, processors, and the operating system embedded in a product (Porter and Heppelmann 2014, 67). These components collect data concerning a product’s condition, use, and environment. Connectivity components include ports, antennae, and communication protocols (Porter and Heppelmann 2014, 67). These components enable smart products to send and receive data (e.g. product updates).

As an example of a smart product, consider a Tesla car. A Tesla car has sensors that constantly monitor the vehicles environment and performance, including the state of its physical components and the manner in which the vehicle is used, as well as traffic, road, and weather conditions. Smart and connectivity components enable the car to continually share data about its condition and use with the manufacturer. The presence of these components makes it possible, for example, to service the car when doing so is actually required, not at predetermined intervals. For example, the vehicle might indicate that an oil change is necessary based on the performance, viscosity, and working temperatures of the oil, thus preventing unnecessary changes of oil that could still be used.[3] When a car service is required, the vehicle schedules an appointment with a mechanic and notifies the owner for confirmation. There is even a Mobile Service option that allows a car to be serviced by a mechanic at the vehicle’s location,

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[2] https://www.hotcars.com/20-biggest-recalls-in-car-history-ranked/

[3] https://www.wired.com/insights/2014/02/teslas-air-fix-best-example-yet-internet-things/

thus avoiding the need to drive it to the mechanic. Another example of improved capabilities and value is the ability that the manufacturer has in some cases to improve the performance of these cars, and fix issues over Internet, without the need to recall the cars. For instance, a car magazine tested a Tesla car and reported poor braking performance.[4] A few days after the test, Tesla updated the car's software over the Internet, recalibrating its braking algorithm and thus instantly improving its braking performance. These examples illustrate some of the differences between conventional and smart products.

The Industry 4.0 transformation is not restricted to smart products but also affects enterprises (Porter and Heppelmann 2015). An enterprise comprises different functional units. In the manufacturing industry, the functional units within an enterprise work to deliver products and services. The research and development (R&D) functional unit researches new technologies and designs new products (Porter and Heppelmann 2015). It develops product specifications, bill of materials, and computer-aided design models. The manufacturing functional unit uses these specifications to manufacture the product. The sales functional unit is responsible for market analysis and selling the product. The information technology (IT) functional unit manages the enterprise-wide computing infrastructure (Porter and Heppelmann 2015) that supports the work of other functional units. The service functional unit provides after-sale services to customers (Porter and Heppelmann 2015).

For enterprises, embracing the Industry 4.0 transformation means evolving into digital enterprises:

> A digital enterprise is an enterprise that applies data and information for the enhancement of the enterprise's products, processes, and services. A digital enterprise leverages digital models of the enterprise to support the use of data and information and facilitate integration among functional units and other digital enterprises.

The transformation into a digital enterprise revolves around the application of data and information from functional units and smart products to enhance an enterprise's performance. In this transformation, data from smart products is fundamental because it can generate insights that can help to improve the performance of the enterprise and its partners and increase the value offered to its customers (Porter and Heppelmann 2015, 103). For example, smart products can be better controlled and optimized through software updates (Porter and Heppelmann 2015, 103).
To apply data and information in a digital enterprise, digital models, feedback loops, and integration among functional units are required. Digital models are models that represent an enterprise and its products, processes, and services. Practitioners refer to

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[4] https://www.wired.com/story/tesla-model3-braking-software-update-consumer-reports/

these models as the "digital twin of an enterprise". A digital twin is defined as "a dynamic software model of a thing that relies on sensors and/or other data to understand its state, respond to changes, improve operations and add value" (Kerremans and Kopcho 2017, 3). Feedback loops are the data and information that are the output of a product, service, or process that are used as input for a product, service, or process. In a digital enterprise, these feedback loops often involve data and information from different functional units and enterprise information systems. Enterprise integration is "the process of ensuring the interaction between enterprise entities necessary to achieve domain objectives" (Chen, Doumeingts, and Vernadat 2008, 648). Enterprise integration can be achieved at different levels (Chen, Doumeingts, and Vernadat 2008), such as physical integration, application integration, and business integration. Integration can be achieved using models (Chen, Doumeingts, and Vernadat 2008). Enterprise interoperability is "the ability for two systems to understand one another and to use functionality of one another" (Chen, Doumeingts, and Vernadat 2008, 648). Such interoperability implies that one system (in this case, a functional unit) performs an operation for another system (Chen, Doumeingts, and Vernadat 2008, 648). Interoperability involves three different levels: data, services and processes. Enterprise integration and interoperability respectively refer to two different degrees of coupling, "tightly coupled" and "loosely coupled". In this thesis, the term integration is used to refer to both concepts. What is important is that functional units integrate with other functional units to enhance an enterprise's performance (as opposed to working in silos).

In a digital enterprise, functional units have new goals (Porter and Heppelmann 2015), and digital models, feedback loops, and integration play an important role in achieving these goals. As shown in Figure 1, in an enterprise that offers normal products, there is no communication from the product to the enterprise, and the limited communication that occurs across functional units is one-directional. One functional unit produces output that is used by another functional unit without timely feedback loops. The same figure indicates that, in the case of a digital enterprise that manufactures smart products, there is communication from the smart product to the enterprise, as well as communication between smart products and/or with other enterprises. In addition, the frequent communication that occurs across functional units is two-directional. Feedback loops are in place, and functional units are integrated. In a digital enterprise, functional units rely on each other to a significant degree. For instance, the R&D functional unit is responsible for integrating in new products connectivity and smart components, as well as for developing features that leverage these components. The IT functional unit needs to provide the infrastructure required by these components. The service functional unit creates new after-sale services that leverage the new components and product data.

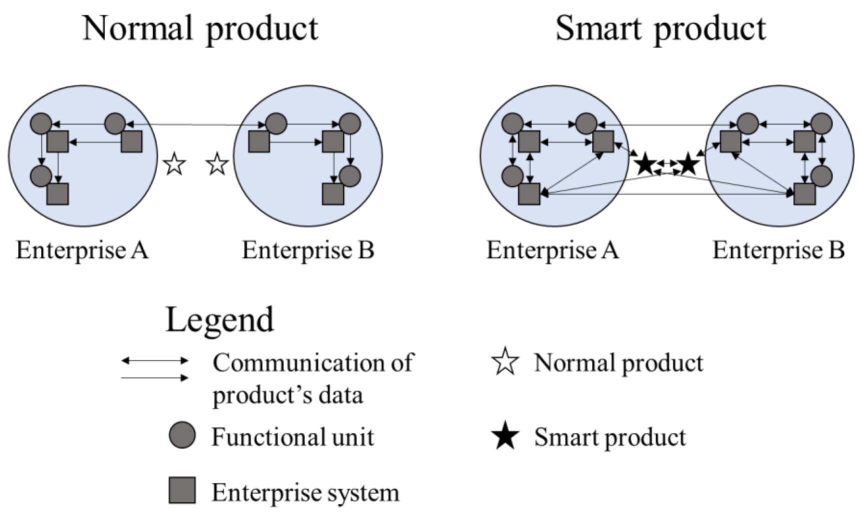

Figure 1. Communication among functional units, enterprise information systems, smart products, and enterprises.

The Industry 4.0 transformation of an enterprise is illustrated using the example of Tesla. Its R&D functional unit develops cars with connectivity components that share data about a car's conditions, use, and environment with Tesla. The R&D functional unit developed a variety of modes for these cars, and it receives feedback from customers on these modes. For instance, a Tesla car has a remote heating mode that allows its owner to remotely activate the vehicle's heating system through a mobile app.[5] This is possible because Tesla has a digital model of every car it produces. This digital model manages and organizes the data about the car.[6] The data communicated from the car to Tesla is used in a feedback loop that provides insights with which the vehicle can be improved. The remote heating mode would not have been possible were the functional units within the enterprise not integrated. Research and design and IT functional units need to be integrated such that the IT department can provide the connectivity infrastructure necessary to establish connections among the company, its vehicles, and its customers.

In the thesis, the Industry 4.0 transformation is defined as follows:

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5 https://eu.usatoday.com/story/tech/2019/04/26/tesla-software-updates-feel-like-new-car-mode-list/2882449002/

6 https://assets1.csc.com/big_data/downloads/MD_9726a-17_Digital_Twin_White_Paper_v5.pdf

> The Industry 4.0 transformation refers to an enterprise that manufactures normal products transforming into a digital enterprise that manufactures smart products.

To summarize, the Industry 4.0 transformation involves both products and enterprises (Porter and Heppelmann 2014, 2015). Products are significantly transformed due to the incorporation of smart and connectivity components and thus differ significantly from conventional products. An enterprise is also deeply transformed by smart products and the use of data and information to enhance its performance. Digital enterprises improve their performance through digital models, feedback loops, and integration. In a digital enterprise, functional units are integrated using digital models and feedback loops. The Industry 4.0 transformation requires each functional unit to jointly transform with other functional units (Porter and Heppelmann 2015). It is an enterprise-wide transformation. For instance, had the IT functional unit not deployed the connectivity required by customers, Tesla, and cars manufactured by the company, it would not have been possible to offer new modes and services.

Enterprise architecture (EA) is a preacademic discipline that aims to support the implementation of enterprise-wide transformations. Enterprise architecture involves the creation of digital models of the enterprise. Enterprise architecture models structure and represent functional units, their processes, and enterprise information systems. Enterprise architecture can also support the development and implementation of feedback loops, as well as the integration of functional units using EA models. Therefore, it can be said that EA serves as the foundation for the Industry 4.0 transformation and that it plays a key role in implementing this transformation within digital enterprises.

1.2. DIGITAL MANUFACTURING

The manufacturing functional unit performs “the process of converting raw materials, components, or parts into finished goods that meet a customer's expectations or specifications”. [7] This functional unit leverages a man-machine setup for large-scale production. Continuing with the example of car manufacturers, their manufacturing processes often aim at minimizing costs,[8] and their production lines often remain unchanged for several years.[8]

> Digital manufacturing is the application of data and information for the enhancement of manufacturing products, processes, supply chains and

[7] http://www.businessdictionary.com/definition/manufacturing.html

[8] https://www.forbes.com/sites/michelinemaynard/2015/08/19/4-differences-between-tesla-and-other-carmakers/

services.[9] It leverages digital models of manufacturing to support the use of data and information and facilitate integration within a digital enterprise.

The transformation to digital manufacturing is based on the application of data and information from enterprise information systems and smart products and equipment to enhance manufacturing. Data from smart products and equipment can provide insights into improving manufacturing and other functional units.
To apply data and information in digital manufacturing, digital models, feedback loops, and integration are required. Digital models in manufacturing represent products, manufacturing processes, components, and resources. Digital models also support access to data in enterprise information systems and the use of data and information for enhancing products and processes. Both the manufacturing unit and other functional units are involved in feedback loops. The data and information about a product or process provided by the manufacturing functional unit are used as inputs in other functional units. Finally, integration in manufacturing requires a shift from working in silos to a way of working that is integrated with other functional units.

Considering the example of Tesla, the company has a digital model of every car it manufactures. Data from the equipment assembling a car is communicated to this digital model so that accurate data about the assembly process is collected. For instance, the torque applied during assembly for every part fitted is collected.[10] In the event of quality issues, the data in the digital model can be used to provide feedback to the production line and adjust the level of torque applied when assembling certain parts. This adjustment requires the functional unit managing the cars' digital models and data to be integrated with the manufacturing functional unit to allow the company to continuously learn about and improve its cars and assembly processes.[8]

To understand enterprises' efforts to achieve digital manufacturing, the author and his supervisors examined 21 enterprises and collaborated with eight of them. These enterprises mostly operate in the manufacturing industry; they range from small and medium enterprises to large international enterprises. Based on the interviews conducted and data gathered, the challenges related to digital manufacturing can be classified into three types: (1) information availability, (2) process and data heterogeneity, and (3) silo mentality.
First, the information availability challenge relates to difficulties in accessing manufacturing information stored in enterprise information systems, a lack of understanding of manufacturing's resources and processes, and a lack of

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[9] https://www.ifm.eng.cam.ac.uk/research/digital-manufacturing/what-is-digital-manufacturing/

[10] https://ftalphaville.ft.com/2018/08/16/1534435108000/Here-s-what-s-really-going-on-in-Tesla-s-factory/

standardization of manufacturing information.
Second, the process and data heterogeneity challenge has been observed in the manufacturing functional units of large manufacturing companies. In these cases, production sites operate in different countries with different regulations, cultures, and historical conditions (Ghoshal and Nahria 1989, 323). Sharing and comparing processes and data within a functional unit is problematic, and it is even more challenging to share and compare processes and data across functional units. In manufacturing, process heterogeneity refers to differences in terms of processes across production sites (Nardello et al. 2019b). In manufacturing, data heterogeneity refers to the inconsistent storage of data on different enterprise information systems (Nardello et al. 2019b). Process and data heterogeneity are mostly due to different environmental and historical conditions (Nardello et al. 2019b).
Third, the silo mentality challenge relates to a lack of interest in pursuing collaboration across functional units and diffidence with regard to openly sharing data and information.

To better describe the three challenges identified above, the following paragraphs present examples of each. First, manufacturing companies have reported difficulties in accessing information because there are few people who know how to use an enterprise information system well enough to extract the required information. Another company reported that they lack an understanding of their production processes and equipment because production process models are developed only when a product is being developed, and these models are not kept aligned with the process used at the production site. An example of a lack of standardization is the lack of unique identifiers, for resources, processes, customers, and parts. For instance, in one enterprise, depending on the enterprise information system on which the information was stored, clients were identified through addresses, internal identification numbers, or national identification numbers. As a result, the enterprise does not know whether a customer has bought the correct product for the software licence they are selling because the customer is identified in different ways in the enterprise resource planning (ERP) system and the customer relationship management system.
Second, several companies encountered the challenge that, while production equipment and parts number are identified according to a rigid convention, the naming of and level of detail concerning processes in these companies' respective enterprise information systems and documentation are not standardized. Therefore, it is often the case that the same production process used at different sites is documented at different levels of detail and using different names for the activities in the process. As a result, production processes are extremely difficult to understand and compare. Furthermore, production processes are often specified differently for each production site. As a result, the data collected during the production process and documentation for the production process was also very different, despite the fact that the same product was being manufactured. This challenge hinders the comparison of production processes.

In addition, it made it problematic for production managers to share data from heterogeneous processes when attempting to achieve process efficiency.
Third, the service functional unit focused almost exclusively on its goals, refusing to share data and information with the R&D functional unit. Therefore, the R&D functional unit had limited insight into how their products were used.

While digital manufacturing requires digital models, feedback loops, and integration, the manufacturing functional units in enterprises experience a lack of information availability, process and data heterogeneity, and silo mentality challenges. These challenges affect the transformation to digital manufacturing. The relationships among digital manufacturing and the challenges are summarized in Figure 2.
As shown in Figure 2, the development of digital models is affected by the information availability challenge. The difficulty in accessing data and information in the first place hinders the development of digital models representing data and information and support access to data and information. A lack of understanding of the resources and processes involved in manufacturing limits the development of digital models of manufacturing's products, processes, components, and resources. Digital models are based on data and information, and a lack of standardization hinders their development.
As is also shown in Figure 2, the development of digital models is also affected by the process and data heterogeneity challenge. The fact that processes vary across production sites complicates the development of digital models representing manufacturing processes. The fact that data is stored inconsistently on multiple enterprise information systems also complicates the representation of data in digital models and the use of data for enhancing products and processes.
Furthermore, there are two additional requirements for digital models. As shown in Figure 2, digital models need to provide operational support for enhancing manufacturing products and processes. Operational support refers to the monitoring of products, resources, and processes to keep them running and manage errors and problems. In addition, the extensive application of digital models requires efficient modelling approaches.
Furthermore, Figure 2 also shows that feedback loops and integration are affected by the silo mentality challenge. Enterprises encountering these problems rely on solutions intended to address information availability and process and data heterogeneity challenges. Once solutions for these challenges are available, incentives for promoting collaboration across functional units and openly sharing data and information need to be developed.

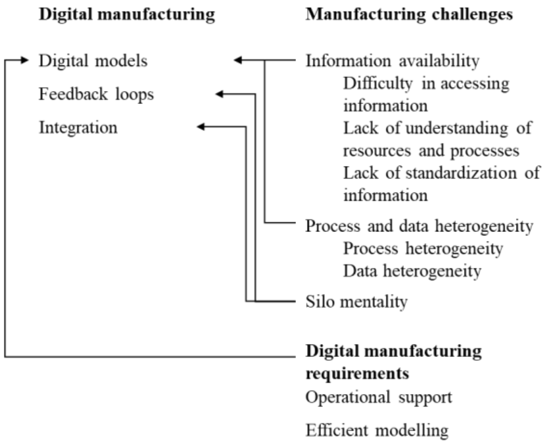

Figure 2. Relationship among digital manufacturing, its requirements, and manufacturing challenges.

As introduced in Section 1.1, EA supports the implementation of enterprise-wide transformations such as the Industry 4.0 transformation. Enterprise architecture can support digital manufacturing by addressing the three challenges encountered in manufacturing presented above. When using an EA, digital models can be used to represent manufacturing's products, processes, components, and resources. The models could be applied to address information availability and process and data heterogeneity challenges. Furthermore, EA models could be further developed to provide the operational support necessary to enhance products and processes.
Using the solutions developed to address these challenges, EA can be applied to address silo mentality. It could also support the development of incentives for promoting collaboration across functional units and openly sharing data and information.

As shown in Figure 3, an EA team can collaborate with functional units to develop EA models representing their key elements, processes, and resources. Enterprise architecture models can represent different aspects of an enterprise. A common EA model is a business process model that identifies the structure of processes and sub-process. These types of models can support the management of process heterogeneity. Other EA models relate to enterprise information systems and data. These models specify the structure and relationship of data and enterprise information systems. These types of models could support the management of data heterogeneity. A common challenge in EA is that EA models are not related to the data stored in an enterprise's information systems, even though these systems support the respective processes of the functional units.

Digital manufacturing revolves around the application of data and information to enhance manufacturing products, processes, supply chains, and services. It relies on digital models, feedback loops, and integration. To support enterprises' shifts to digital manufacturing, the purpose of this thesis is twofold: First, it researches the development of EA models for digital manufacturing to better communicate data and information about manufacturing's products, processes, components, and resources. Second, it investigates the enhancement of EA models to provide the operational support required to enhance manufacturing products and processes. Before the objectives of this thesis are presented, the EA discipline is introduced.

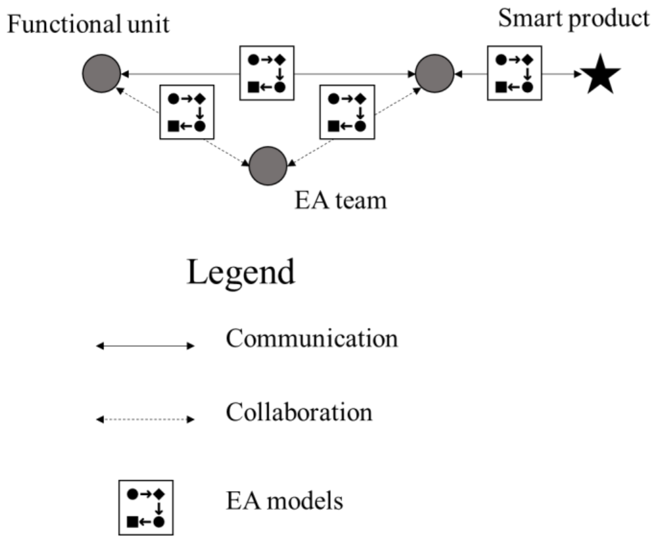

Figure 3. Role of EA in supporting functional unit integration.

1.3. ENTERPRISE ARCHITECTURE

Building upon the ISO/IEC/IEEE 42010 standard (ISO/IEC/IEEE 2011), EA is a discipline that defines the essential elements of an enterprise and the relationships among these elements and the environment in which that enterprise operates, as well as the principles of the enterprise's design and evolution. The aim of EA is to "effectively implement the overall enterprise strategy by designing the various enterprise facets […] to maximize coherency between them and minimize contradictions" (Lapalme 2012, 38).

Initially developed by practitioners and policy-makers, EA is a preacademic discipline that has been researched in academia over the last 30 years. For this reason, insights from practitioners have played an important role in the development of the discipline. Therefore, this thesis includes discussions with enterprise architects and EA consultants.

Enterprise architecture models define an enterprise's elements and relationships. These models are an abstract representation of parts or aspects of the real world (Lankhorst et al. 2017, 143). Given the purpose of EA models, they focus on specific aspects of the real world (Lankhorst et al. 2017, 143). These models are generally divided into three aspects (Lankhorst et al. 2017, 76), namely business, application, and technology. Models related to the business aspect focus on an enterprise's strategy, organisational structure, products and services, and business processes. Models related to the application aspect focus on the applications (software) required to support business processes (e.g. enterprise resource planning). Models related to the technology aspect focus on the infrastructural services required by these applications. Enterprise architecture models can include elements and relationships that represent both an existing enterprise as well as future scenarios that it might face. It is possible to distinguish between as-is and to-be EA models. An as-is model represents the elements and relationships of an enterprise when the model was initially developed. To-be models represent the elements of and the relationships in a future desirable state of the enterprise. By investigating these various aspects, EA practitioners can provide recommendations to executives and identify projects by which to implement the intended enterprise strategy (Gartner Inc. 2017). For instance, EA models make it possible to analyse an enterprise by focusing on certain aspects and guide the development and implementation of enterprise information systems.

Enterprise architecture discipline leverages different methodologies. In summary, they start with the definition of the purpose of the application of EA in an enterprise. Thereafter, they require the modelling of different aspects of that enterprise (i.e. business, application, and technology aspects). The EA models used to represent these aspects can be classified as current, as-is models and future, to-be models. Using these models, initiatives intended to transform an enterprise from its current as-is state to the future to-be state are defined. These initiatives are part of the transformation plan. The last part of the methodologies relates to managing the implementation of the plan. The EA team is responsible for applying the methodology required to implement the enterprise strategy. The team is usually composed of architects and professional who have competences covering the different aspects of an enterprise.

A key responsibility of the EA team is EA modelling. In a nutshell, this process is used to create EA models (Lankhorst et al. 2017, 145). It usually starts by defining the purpose, scope, and concepts of an EA model (Lankhorst et al. 2017, 145). It continues with the identification of stakeholder requirements. Thereafter, the EA model is created and visualized in a way that can be understood by the stakeholders. Finally, this visualization of the EA model is used to communicate with the stakeholders. Traditionally, EA modelling has been a manual process, which made EA modelling inefficient, time-consuming, and error-prone (Hauder, Matthes, and Roth 2012; Buschle et al. 2012; Hauder et al. 2013; Holm et al. 2014). This problem has been identified as one of the major challenges in EA (Farwick et al. 2016, 397), and it is therefore critical to reduce the number of manual activities in this process

(Perez-Castillo et al. 2019). Recently, automated EA modelling methods (Buschle et al. 2011; Farwick et al. 2016) have been used to address this problem.

Achieving the overall purpose of this thesis involves addressing three main aspects. The first is determining which EA models can be used for modelling smart products and digital enterprises. The second aspect relates to the use of data to create EA models for digital manufacturing. Finally, the third aspect relates to the use of data to enhance EA models for digital manufacturing.

1.4. THESIS OBJECTIVES

The Industry 4.0 transformation requires functional units to transform themselves and integrate with other functional units (Porter and Heppelmann 2015). The transformation to digital manufacturing revolves around the application of data and information to enhance manufacturing and requires digital models, feedback loops, and integration. As presented in Section 1.2, enterprises are facing challenges that may impact their shift to digital manufacturing. Enterprise architecture discipline can be helpful in addressing these challenges, supporting such transformations, and facilitating the development of digital models and feedback loops and promote integration. The purpose of this thesis is twofold: First, it explores the development of EA models intended to support digital manufacturing. The use of such models is intended to better communicate data and information about manufacturing's products, processes, components, and resources. Second, it investigates the enhancing of EA models to provide the operational support required for improving manufacturing products and processes. This thesis focuses on these models because they serve as the foundation for developing feedback loops and integration. The overall goal of this thesis is broken down into three thesis objectives which are summarized in Figure 4.

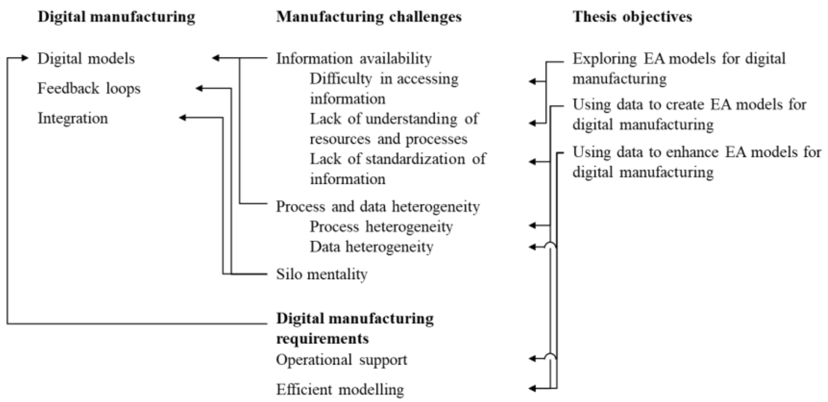

Figure 4. Relationships among digital manufacturing, its requirements, manufacturing challenges, and the three thesis objectives.

The first objective is to explore the development of EA models as digital models for digital manufacturing. As explained in Section 1.2, digital models represent products, processes, components, and resources. They support access to data in enterprise information systems, as well as the use of data and information for enhancing products and processes. Therefore, exploring the development of EA models for representing products, processes, components, and resources and the use of EA models for communicating data and information is fundamental for the transformation to digital manufacturing. The exploration of EA models as digital models for digital manufacturing requires contributions that address the information availability challenge.

The second objective is to research the use of data to create EA models for digital manufacturing. Manufacturing processes are managed through enterprise information systems. Since digital manufacturing revolves around the use of data and information stored in these systems, EA models could be based on this data. Using this approach, EA models would be directly related to the data and information stored on such systems. However, the number of EA models that it would be necessary to create would require the application of efficient modelling approaches. As mentioned in Section 1.3, automated EA modelling methods can be created based on data; however, new research is required to create EA models for digital manufacturing. When using data to create EA models for digital manufacturing, it is necessary to address the information availability and process heterogeneity challenges, as well as to satisfy the requirement of an efficient modelling approach for creating digital models.

The third objective of this thesis is to research use data to enhance EA models for digital manufacturing. In digital manufacturing, digital models are related to data stored on enterprise information systems to support the use of data and information to enhance products and processes. Therefore, EA models need to provide operational support for enhancing manufacturing products and processes. When using data to enhance EA models for digital manufacturing, it is necessary to address the data heterogeneity challenge, as well as to ensure that the digital models satisfy the requirements of providing operational support and efficient modelling.

To achieve these three objectives, three empirical contexts are considered. The first context is manufacturing companies that are members of the Manufacturing Academy of Denmark (MADE). This association focuses on the development of innovative manufacturing solutions in Danish industry.[11] It does so through conducting applied industrial research projects. This focus led to the research efforts made for this thesis being directed towards applied research with the potential for industrial applications. The author collaborated with several MADE manufacturing companies. Based on

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[11] https://en.made.dk/about-made/

these collaborations, it was acknowledged that digital manufacturing and digital enterprises are still important goals for these manufacturing companies. The second context is represented by QualiWare ApS. QualiWare ApS develops a leading EA repository,[12] and they have followed and contributed significantly to the research presented in this thesis. The research conducted for his thesis leveraged their EA repository and their employees' knowledge and expertise. The third context is the learning factory at Aalborg University. This context resembles a real production environment, and it was used to develop artefacts for digital manufacturing. These three contexts encounter different problems and had different influences on the research conducted for this thesis. These aspects are discussed in Chapter 3 and 8.

1.5. THESIS STRUCTURE

Based on the objectives identified above, this thesis is structured as shown in Figure 5. The introductory chapter explained this thesis' key topics, namely smart products, digital enterprises, digital manufacturing, and EA. The theoretical framework chapter presents concepts and research that were identified as being most relevant to each of this thesis' objectives. This chapter aims at providing the reader with a basic understanding of state-of-the-art research related to each objective, identifying research gaps, and positioning the research contributions of this thesis. The research design chapter discusses the philosophy of science, design science research methodology, and the goals and choices made regarding the research design of this thesis. This chapter concludes by presenting the research questions addressed in this thesis. The following three chapters (4, 5, and 6) present the contributions of the six articles included in the thesis to each of this thesis' objectives. Each chapter focuses on one objective, discussing the research and practitioner context, the problem explored, the contribution(s) made by the relevant articles, the role played by each contribution in the "building blocks" of this thesis, and a reflection on the work performed. The synthesis chapter uses the "building blocks" presented in the previous chapters to summarize the contributions of this thesis. The following chapter evaluates the contribution of the research conducted for this thesis by comparing it with the research design chapter. In addition, it describes the significance of the research presented in this thesis, its implications for practitioners, its limitations, future research directions, and a reflection on the on the entire PhD studies. Finally, the conclusion chapter summarizes the contributions of this thesis.

[12] https://www.gartner.com

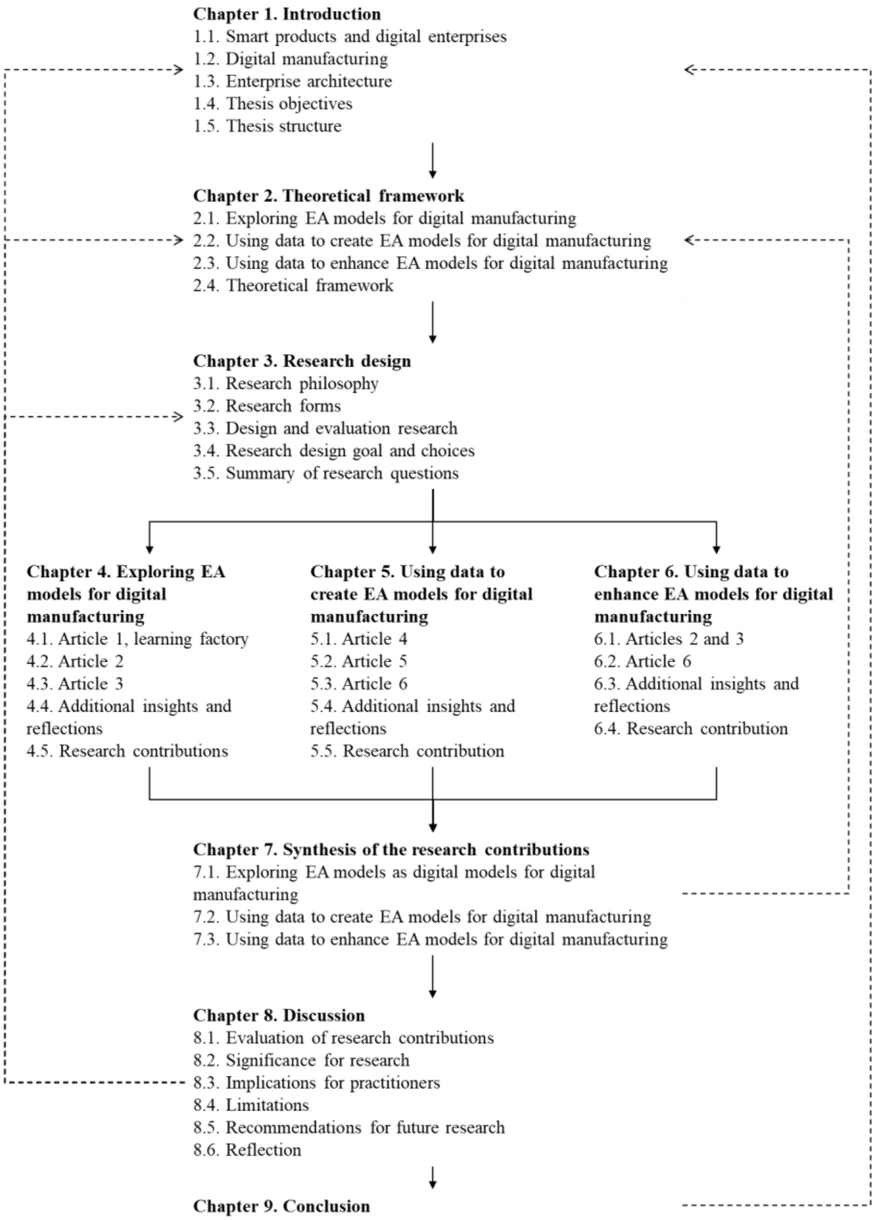


Figure 5. Thesis structure. Full arrows represent the flow and connections between chapters. Dashed arrows represent additional connections between chapters.

CHAPTER 2. THEORETICAL FRAMEWORK

This chapter presents the main concepts and research gaps related to the three EA objectives of the thesis: (1) exploring EA models for digital manufacturing, (2) using data to create EA models for digital manufacturing, and (3) using data to enhance EA models for digital manufacturing. The last section synthesizes the research gaps in a theoretical framework that is used throughout the remainder of this thesis.

This chapter summarizes the concepts identified as being the most important in terms of providing the reader with a basic understanding of the three objectives of this thesis. This summary, however, makes no pretence of being exhaustive. Each section concludes by presenting research gaps relevant to its themes. In this thesis, research gaps are understood as unexplored or underexplored research areas. The first section of this chapter presents EA models and reference architecture models for digital manufacturing. The second section presents automated EA modelling and process mining research relevant for using data to create EA models. The third section presents automated EA modelling and process mining research relevant for using data to enhance EA models. The final section summarizes the research gaps associated with each objective.

2.1. EXPLORING EA MODELS FOR DIGITAL MANUFACTURING

This section addresses the first objective of the thesis. Digital models for digital manufacturing represent products, processes, components, and resources. As presented in the example of Tesla, such models support access to data in enterprise information systems, as well as the use of data and information for enhancing products and processes. As discussed in **Error! Reference source not found.**, exploring the d evelopment of EA models as digital models and their use for communicating data and information is fundamental for the transformation to digital manufacturing. Enterprise architecture models are well-suited for digital manufacturing since they are already being used to model enterprises' goals, processes, products, and resources. Reference architecture models are important in this context because they define the content and structure of EA models. This allows EA models to be consistent and related to each other.

2.1.1. EA MODELS

A model is "a purposely abstracted and unambiguous conception of a domain" (Lankhorst et al. 2017, 48). A domain is "any subset of a conception (being a set of elements) of the universe" (Lankhorst et al. 2017, 48). Therefore,

> An EA model is a purposely abstracted and unambiguous conception of a set of elements of or related to an enterprise.

Enterprise architecture models focus on different elements and cover three main aspects of an enterprise (Lankhorst et al. 2017, 76). The business aspect of EA models covers and enterprise's products and services and the business processes required to deliver them (Lankhorst et al. 2017, 76). The application aspect models the software applications, as well as the components thereof, that are deployed to support business processes (Lankhorst et al. 2017, 76). The technology aspect models the infrastructural technologies (e.g. processing, storage, and connectivity) necessary to run the software applications (Lankhorst et al. 2017, 76).

2.1.2. REFERENCE ARCHITECTURE MODELS

Reference architecture models define the structure and content of EA models, as well as their relationships with other EA models. Three reference architecture models are considered particularly relevant for digital manufacturing.

The Generic Enterprise Reference Architecture and Methodology (GERAM) defines elements related to an enterprise to be used in enterprise engineering and integration projects (Lankhorst et al. 2017, 31). The main elements are organized into three categories: The human-oriented elements describe humans' role as part of an enterprise and its operation (Lankhorst et al. 2017, 31). They support humans in designing, constructing, and changing an enterprise (Lankhorst et al. 2017, 31). The process-oriented elements describe the business processes of an enterprise (Lankhorst et al. 2017, 31). Finally, the technology-oriented elements describe the technology supporting an enterprise's operations and engineering efforts (Lankhorst et al. 2017, 31).

The Reference Architecture Model Industry 4.0 (RAMI4.0) defines the elements of the assets of an enterprise (International Electrotechnical Commission 2017). An asset refers to any object that has value for an enterprise (International Electrotechnical Commission 2017). An asset can be tangible, such as a product or equipment, or intangible, such as software or data. RAMI4.0 is structured in three dimensions: architecture, life cycle and value stream, and hierarchy levels. The architecture dimension includes six aspects of an asset (International Electrotechnical Commission 2017). The business aspect describes an asset's commercial information (e.g. its price, availability, and legal and regulatory conditions). This aspect also includes business processes and business models related to the asset. The functional aspect provides a digital description of both the logical and technical functions of an asset (e.g. its integration with other assets, as well as runtime data concerning processes, functions, and applications). The information aspect relies on data concerning the technical functionalities of an asset. In this context, a distinction is made between non-real-time and real-time data. Non-real-time data concerns execution rules and interfaces for data communication, while real-time data refers to production data and data relevant to the functional aspect. The communication aspect describes “the access to information and functions of a connected asset by other assets” (International Electrotechnical Commission 2017). This aspect specifies the data to be considered, its use, and communication. The integration aspect models the physical-information relationship, meaning that physical changes are represented as information. The asset aspect digitally represents physical assets, such as a product or production equipment.

The life cycle and value stream dimension distinguishes between product type and product instance information. The first focuses on common characteristics shared among all types of that asset (e.g. product part ID), while the second relates to the properties of individual instances (e.g. product serial number). This distinction is used in RAMI4.0 to structure the life-cycle model in four phases: development, sales, after-sale support, and obsolete.

The hierarchy levels dimension uses the ISA-95 hierarchy. It structures asset information at different levels: product and field device, control device, station, work centres, enterprise, and connected world.

The Industrial Internet Reference Architecture (IIRA) is a standard-based open architecture with broad industry applicability (Technology Working Group Industrial Internet Consortium 2017). It is intended to “drive interoperability, to map applicable technologies, and to guide technology and standard development” (Technology Working Group Industrial Internet Consortium 2017, 10). Its elements cover four aspects to support a digital transformation to “bring industrial control systems online to form large end-to-end systems” (Technology Working Group Industrial Internet Consortium 2017, 9). Similarly to RAMI4.0, IIRA supports the connection of industrial control systems, along with people integrating them, with an enterprise’s information systems, business processes, and platforms. The business aspect models stakeholders and their business visions, values and objectives in pursuing a digital transformation (Technology Working Group Industrial Internet Consortium 2017, 16). The usage aspect relates to system usage; it models the fundamental system capabilities and the sequences of activities involving either human or logical users required to deliver them (Technology Working Group Industrial Internet Consortium 2017, 16). The functional aspect “focuses on the functional components in an IIS, their interrelation and structure, the interfaces and interactions between them, and the relation and interactions of the system with external elements in the environment, to support the usages and activities of the overall system” (Technology Working Group Industrial Internet Consortium 2017, 16). The implementation aspect models the technologies required by the “functional components, their communication schemes and their lifecycle procedures” (Technology Working Group Industrial Internet Consortium 2017, 16).

There are two main limitations related to the objective of exploring EA models for digital manufacturing: The first limitation concerns EA and EA and its failure to take into account the entirety of an enterprise. The EA discipline emerged as a response to the need to define the IT architectures of enterprises. Although the discipline has evolved since its original conception, in most enterprises, EA is included or closely related to the IT functional unit. Furthermore, even though EA models cover the business, application, and technology aspects, they are largely focused on the IT aspect. For instance, EA models related to the application and technology aspects usually focus on enterprise information systems, data, servers, and networking technologies. Manufacturing processes, resources, and IT are often not included in EA models. Researchers have identified the need for EA to develop a deeper understanding of and to include other disciplines and functional units within an enterprise (Gøtze 2013).

The second limitation is in manufacturing, and it relates to new smart product components (i.e. smart and connectivity components) that need to managed and leveraged. In addition to the physical components in products, resources, and equipment, smart products and equipment have smart and connectivity components (Porter and Heppelmann 2014, 2015). These components introduce new aspects in manufacturing related to smart products and equipment operating systems, data, and integration. These aspects are closely related to EA and EA models.

The EA and manufacturing limitations uncover new research gaps. Enterprise architecture models may be adequate for modelling manufacturing and new aspects thereof. The new aspects of smart product and equipment could be modelled with EA models pertaining to the application and technology aspects. Simultaneously, EA models might be able to model manufacturing processes, resources, and IT infrastructure. This ability would be important for manufacturing because it would enable equipment and the data and performance thereof to be related to production processes, which would create an important data source for the improvement of production processes. A fundamental starting point for modelling digital manufacturing is reference architecture models. They define the key aspects to be modelled and the structure of EA models. However, when the research conducted for this dissertation commenced in 2016, the new reference architecture models for digital manufacturing (i.e. RAMI4.0 and IIRA) were under development, and no applications or evaluations thereof were available to the research community. Furthermore, industrial applications of EA models for modelling digital manufacturing were not available. A possible explanation for the lack of industrial applications could be that enterprises had only recently started shifting to digital manufacturing and had not yet developed digital models. Regardless, insights into modelling digital manufacturing will likely prove valuable once enterprises have further progressed with their Industry 4.0 transformation.

2.2. USING DATA TO CREATE EA MODELS FOR DIGITAL MANUFACTURING

This section addresses the second objective of the thesis, namely using data to create EA models for digital manufacturing. Enterprise architecture models for digital manufacturing represent products, processes, components, and resources and take into considerations different aspects, such as those related to business, application, and technology. These EA models aim at supporting the use of data and information for the enhancement of manufacturing products and processes. As discussed in **Error! Reference source not found.**, EA models can be created directly from data stored in manufacturing enterprises' information systems. By visualizing and managing the data stored on enterprises' information systems, the research conducted for this objective addresses the lack of standardization of information in such systems. Furthermore, since these systems manage production processes, this research could also address the process heterogeneity problem and fulfil the requirement of efficient modelling in digital manufacturing. The starting point for achieving this objective is automated EA modelling methods and process mining. The former emerged as a response to the traditional manual process of creating EA models. As a manual process, EA modelling is inefficient, time-consuming, and error-prone (Hauder, Matthes, and Roth 2012; Buschle et al. 2012; Hauder et al. 2013; Holm et al. 2014). Process mining focuses on event logs for extracting insights about processes.

2.2.1. AUTOMATED EA MODELLING

The two methods presented above represent the most developed methods in this domain. Automated EA documentation (Farwick et al. 2016) focuses on the collection of the data necessary for the creation of EA models. The method includes four techniques (Farwick et al. 2016): (1) task-based reminders, (2) automated structured data collection, (3) external event triggers, and (4) internal model event triggers. Techniques 1, 3, and 4 inform users that a revision of an EA model is needed. The automated structured data collection technique focuses on "the reuse of external structured data sources into the EA model in order to reduce or even eliminate the manual data collection effort for specific model elements in the repository" (Farwick et al. 2016, 408). The technique consists of three main activities: (1) importing data from the data source to the EA repository, (2) evaluating whether manual intervention is necessary; and (3) instantiating elements in an EA repository.

The automated EA modelling method focuses on the creation of EA models related to the IT architectures of enterprises (Holm et al. 2014, 839). The method was outlined by Buschle et al. (Buschle et al. 2011) and further applied and developed by other researchers (Holm et al. 2014; Välja et al. 2015, 2016). This method relies predominantly on network scanner applications to collect data concerning the IT architecture of an enterprise (2011). Using ArchiMate modelling notation and the collected data, the method creates elements in the EA Analysis Tool (EAAT) repository. The method starts by mapping fields from the data source to ArchiMate's fields. It then instantiates the data collected into elements in the EAAT repository and creates EA models.

These methods can be applied to create EA models for digital manufacturing. For instance, automated EA modelling methods seems applicable for modelling technology aspects, such as the communication aspect in RAMI4.0 (International Electrotechnical Commission 2017). The communication aspect focuses on how information is communicated and the method models IT architectures and communication between applications. However, these methods have three main gaps when applied to digital manufacturing. Their first gap is the fact that, while these methods focus on the application and technology aspects, they do not model the business aspect. In digital manufacturing, the business aspect includes concepts such as production processes, product components and the equipment used in the production processes. Should these needs not be taken into consideration, EA models of components and equipment will be isolated and unrelated to the business aspect and to manufacturing processes. Therefore, these methods do not address an important aspect of EA models. The second gap relates to the fact that data in enterprise information systems is excessively detailed for the creation of EA models. Essentially, the data in an EA model will not be understandable if it is included as it is in an enterprise's information systems. Farwick et al. (2016) identified this gap as an important area for future research. The third gap concerns these methods' failure to support the use of reference architecture models and ontologies to structure data and EA models.

2.2.2. PROCESS MINING

Process mining establishes the relationships among actual processes, their data, and process models (Van Der Aalst 2016). Process models are fundamental in understanding the design of processes (Van Der Aalst 2016). In addition, process models are crucial in the configuration and implementation of processes in executable form for the systems controlling them (Van Der Aalst 2016). Furthermore, process models are used to monitor processes and diagnose new problems that need to be addressed (Van Der Aalst 2016). Process mining techniques use event logs containing detailed information about the activities executed in a process to create new knowledge (Van Der Aalst 2016). There are three main types of process mining. The process discovery technique uses event logs to create a model without any a-priory information (Van Der Aalst 2016). This is the most well-known technique, and it is used to discover "real" processes on the basis of process event logs (Van Der Aalst 2016). The conformance checking technique uses an existing process model and compares it with a process' event log (Van Der Aalst 2016). This technique can be applied to determine whether executed processes are aligned with their models and vice versa (Van Der Aalst 2016). It can be applied to various types of models, such as process, procedural, and organizational models, as well as business rules (Van Der Aalst 2016). The model enhancement technique extends and improves process models using the actual process information recorded in event logs (Van Der Aalst 2016). For instance, timestamps in an event log can be used to extend a process model to identify bottlenecks and service levels (Van Der Aalst 2016).

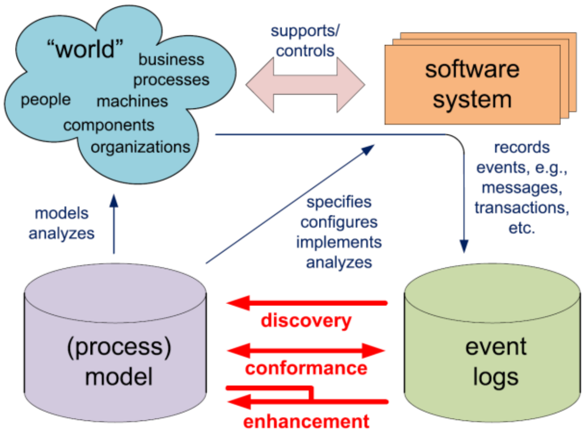


Figure 6. Process mining techniques from (Van Der Aalst 2016, 32)

The process discovery technique is an approach that better addresses the objective of using data to create EA models. A significant contribution to this technique is the use of process abstraction, which provides an overview of a process (Garcia et al. 2019). Related activities are aggregated to represent a process in a compact and understandable way (Garcia et al. 2019). Another significant contribution to the technique is the use of ontology and semantic-based approaches. These approaches aim to enrich event logs with appropriate ontology structures. Using this approach, processes can be represented at different abstraction levels. Examples of these levels include the generic approach of Kingsley et al. (2016) and the approach for organizing maintenance actions developed by Karray et al. (2014).

The process discovery technique has been previously applied in the manufacturing context (Garcia et al. 2019). Reliable event logs can be used to gain insights into an enterprise's processes. In the case of smart products, this technique could be applied to analyse the event logs of a smart product to better understand that product's usage (Garcia et al. 2019). These contributions could be used to address the three gaps associated with automated EA modelling methods. To address the failure to model the business aspect, the logic of the process discovery technique could be used to create a new automated EA modelling method to create EA models pertaining to the business, application, and technology aspects. To address the excessively detailed data in enterprise information systems for the creation of EA models, an overview of the data stored on enterprise information systems could be created using process abstraction, in a manner similar to event logs. Using this approach, detailed data could be represented in a compact and understandable way. To address the failure to support the use of reference architecture models and ontologies, process mining contributions that map event logs to ontologies could be applied. This approach would make it possible to standardize data and make it more understandable.

Process mining includes several solutions that are useful for the objective of using data to create EA models for digital manufacturing. However, there are still three important research gaps to be addressed concerning using data to create EA models for digital manufacturing. The first gap is that neither automated EA modelling methods nor process discovery techniques are generic enough to model all EA aspects, particularly the business aspect. The second gap is that processing mining techniques use event logs as data sources for creating process models. However, such data is constantly changing, and more stable data sources are preferred for the creation of EA models. The third gap is that automated EA modelling methods that are useful for efficient modelling do not take into consideration and contribute to addressing the process heterogeneity challenge in manufacturing companies.

2.3. USING DATA TO ENHANCE EA MODELS FOR DIGITAL MANUFACTURING

This section addresses the third objective of the thesis, namely using data to enhance EA models for digital manufacturing. These EA models aim at supporting the use of data and information for the enhancement of manufacturing products and processes. As discussed in **Error! Reference source not found.**, EA models have the potential t o provide operational support for enhancing manufacturing products and processes. To provide this support, more data and information from different enterprise information systems needs to be included in such models. When attempting to include such data and information, it will be necessary to address the data heterogeneity challenge, taking into consideration the requirement of efficient modelling. The starting point for achieving this objective is the use of the process enhancement technique in process mining.

The process enhancement technique is “focused on extending the process model with relevant information” (Garcia et al. 2019, 268). When using this technique, different perspectives can be added to the process model. The organizational perspective extends the process model to provide insights concerning “people, machines, organizational structures (roles and departments), work distribution, and work patterns” (Van Der Aalst 2016, 281). The time perspective focuses on the timing and frequency of events (Van Der Aalst 2016, 290). For instance, it allows for the discovery of bottlenecks, the analysis of service levels, and the monitoring of resource utilization (Van Der Aalst 2016, 290). The case perspective uses the attributes of events to communicate, for example, the path taken and performance information.

Data heterogeneity creates new challenges for process mining (Becker, Lütjen, and Porzel 2017, 80). General modelling approaches are required to connect information from multiple stakeholders involved in a process (Becker, Lütjen, and Porzel 2017, 81). Becker et al. (2017) developed a process mining approach to constantly update process models used in logistics using heterogeneous data. The process enhancement technique relies on the fact that the event log used to create the process model is the same source used to enhance the model with the additional perspectives. The process enhancement technique and the three perspectives can be used as a foundation to develop an approach for enhancing EA models. Depending on the type of EA model to be enhanced, the technique could allow for the automated addition of documentation and key performance indicators (KPI) to EA models. In addition, the process mining approach (Becker, Lütjen, and Porzel 2017) could be used to address data heterogeneity. However, the authors did not present this approach in enough detail to be implemented.

There are two main research gaps related to this objective: First, automated EA modelling methods and process mining lack an approach that allows data from sources other than the event logs used to create models to be included in the models. Second, they do not adequately consider and contribute to addressing the data heterogeneity challenge experienced by manufacturing companies.

2.4. THEORETICAL FRAMEWORK

This section summarizes and frames this thesis' theoretical framework which is depicted in Figure 7. Given the similarity between process mining and the research presented in this thesis, the framework of process mining techniques was adapted to frame the research gaps addressed in this thesis.

Enterprise architecture models are the core of the theoretical framework and the focus of the first objective of this thesis. The research related to this objective aimed at establishing a relationship between digital manufacturing and EA models. As shown in Figure 7, EA models are important in the design of an enterprise. Furthermore, EA models are used to specify, implement, and analyse enterprise information systems, as well as to monitor enterprises and diagnose problems. As discussed in Section 2.1, there is one main research gap associated with exploring the use of EA models as digital models for digital manufacturing. This gap revolves around the applicability of EA models for modelling digital manufacturing. Specifically, it must be understood whether and why EA models work as digital models for digital manufacturing, and the conditions under which they work must be specified.

Another important part of the theoretical framework is using data from enterprise information systems to create EA models for digital manufacturing. As shown in

Figure 7, enterprise information systems store data that could be potentially used to create EA models. However, as presented in Section 2.2, there are still three important research gaps before this goal can be achieved. The first gap concerns the lack of automated EA modelling methods for creating EA models related to all aspects, especially the business aspect. The second gap relates to the lack of automated EA modelling methods that use the data stored on enterprise information systems as a source for the creation of EA models. The third gap is the lack of automated EA modelling methods for addressing the process heterogeneity challenge in manufacturing companies.

The third important part of the theoretical framework concerns using data from enterprise information systems and event logs to enhance EA models for digital manufacturing. As shown in Figure 7, enterprise information systems and event logs could potentially be used to enhance EA models to provide operational support intended to enhance manufacturing processes and products. However, as discussed in Section 2.3, there are two main research gaps: First, there is a lack of an automated EA modelling method that presents in detail how EA models can be enhanced using multiple data sources. The second gap concerns the lack of automated EA modelling and process mining methods for addressing the data heterogeneity challenge experienced by manufacturing companies.

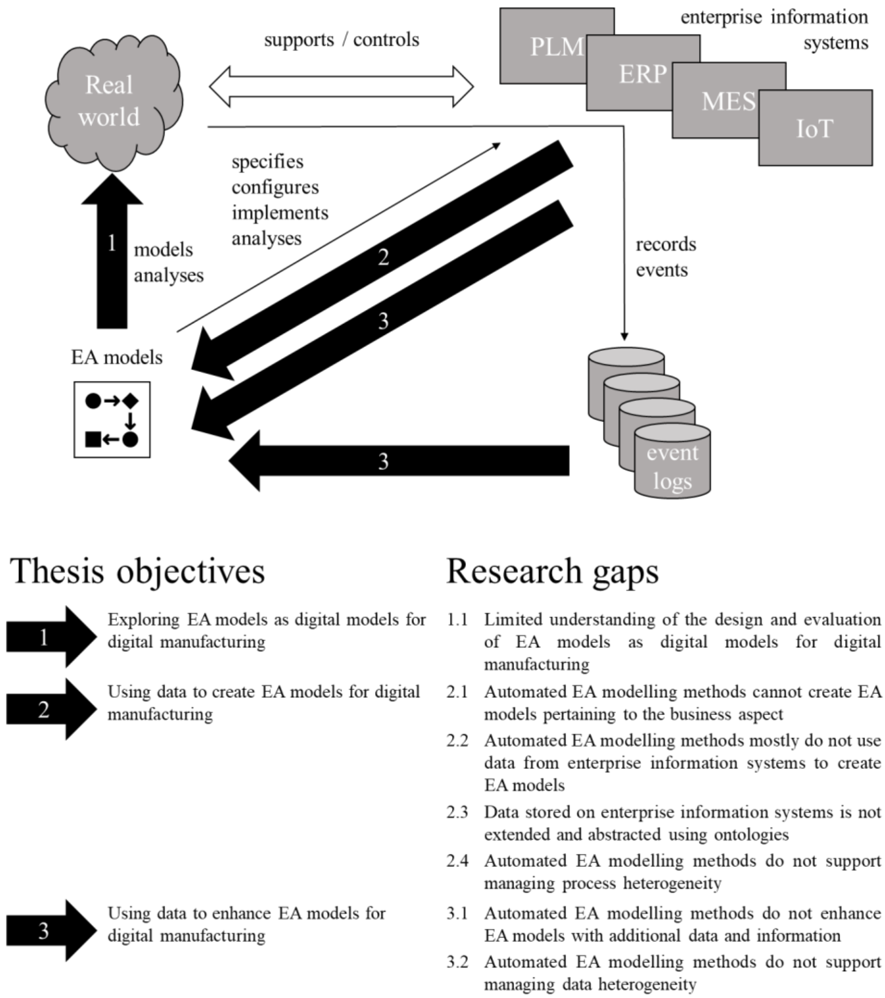


Figure 7. Theoretical framework presenting this thesis' objectives and related research gaps

CHAPTER 3. RESEARCH DESIGN

This chapter clarifies the research philosophy and research design choices in the thesis. Furthermore, it describes the research methodologies, the research design of this thesis, and the research design of each article. The chapter ends with by presenting the overall research questions of this thesis, the research questions for each thesis objective, and the research questions explored in each article. These research questions guide the presentation of the research contributions in the following chapters.

This section begins with an explanation of the nature of the phenomenon examined in this thesis, as well as the methods that can be used to understanding it. It then presents research forms and methodologies that are relevant for EA and the empirical context. These elements are used to explain the research design choices and the framework used for the evaluation of the research contributions.

3.1. RESEARCH PHILOSOPHY

Philosophies of science are grounded on ontologies and epistemologies (van de Ven 2007). Ontologies refer to the nature of the phenomenon examined, whereas epistemologies relate to the methods used to understand the phenomenon (van de Ven 2007, 39). Two dichotomous positions exist in Western philosophies: positivistic and relativistic. Positivism is ontologically objective, meaning that reality is considered to exist independently from the concepts of the scientist. Positivism is epistemologically objective, meaning that reality can be studied without being affected by the scientist. Through objective observations of reality, new knowledge can be obtained and new theories created. In contrast, relativism is ontologically subjective, meaning that reality is considered to be constructed by people and/or society. Reality is created by interactions between individuals. Relativism is epistemologically subjective, meaning that reality and the scientist are interactively connected. The creation of knowledge is dependent on and determined by the concepts of the scientist.

At the core of the nature of EA, there is an enterprise, a "collection of organisations that has a common set of goals and/or a single bottom line" (Lankhorst et al. 2017, 2). An enterprise and its organisational structure, business processes, information systems, and infrastructure exist independently, regardless of whether or not the people involved and the author are aware of them. Therefore, an objective ontological position would be adequate. However, EA is "a coherent whole of principles, methods, and models that are used in the design and realisation of an enterprise's organisational structure, business processes, information systems, and infrastructure" (Lankhorst et al. 2017, 3). The methods and models used to design and realise an enterprise and its organisational structure, business processes, information systems, and infrastructure are dependent on and determined by the concepts of the individuals involved in that enterprise and the enterprise architect. In EA, an enterprise architect applies methods and develops models based on his or her knowledge and subjective understanding of reality. Similarly, the author of this thesis interacted with enterprises, and his understanding of these enterprises is determined by his concepts and knowledge. Therefore, reality exists independently of the author, but the author's understanding of reality is determined by his concepts and knowledge. The author's knowledge of reality is considered to always be incomplete. Theories explain reality, but they are never perfect and can always be substituted by new theories that offer better explanations of reality. Contributions intended to solve a problem can be substituted by new contributions that better solve the problem in question. The selection of better contributions leads to knowledge growth. It is therefore important to evaluate contributions in their real-world environments. However, the diversity that exists among environments (i.e. enterprises) limits the possibilities in terms of generalizing experimental outcomes. The author's understanding of reality improves every time that his contributions are applied. Therefore, a reflexive approach that re-evaluates previous contributions using newer understandings of reality is important. Science in disciplines such as EA is thought of as a process of error correction (van de Ven 2007, 62).

3.2. RESEARCH FORMS

Many research approaches are available. To navigate these approaches, the research forms from van de Ven's framework were selected (van de Ven 2007, 27). These forms were adopted for two reasons: First, the engaged scholarship research approach is deemed relevant in this thesis, as both EA and the approach are related to organizations. Enterprise architecture as a discipline focuses on the design of the organisational structure and processes of an enterprise. Enterprise architecture models capture and are used to design an organization's structure and processes. Therefore, it is important to also take into consideration the organizational context of EA and EA models. The engaged scholarship research approach aims at producing knowledge by encouraging collaboration between researchers and practitioners from an organizational context. Second, there is substantial alignment between the ontological and epistemological positions of engaged scholarship and the positions presented in the Section 3.1.

Engaged scholarship presents four research forms, as shown in Figure 8. The different research forms are distinguished by (1) whether the research conducted for a particular purpose is intended to investigate "basic questions of description, explanation, and prediction" or to address "applied questions of design, evaluation, or action intervention" (van de Ven 2007, 27) and (2) whether the researcher investigates the research problem as “an external observer or an internal participant” (van de Ven 2007, 27). The research purpose (i.e. to explain or design) and perspective (i.e. external or internal) lead to the following four research forms:

1. *Informed basic research* is used to “describe, explain, or predict a social phenomenon” (van de Ven 2007, 27), and the researcher is an external observer of the object of investigation. However, the researcher will usually seek key stakeholders’ advice and feedback during the research activities.
2. *Collaborative basic research* is undertaken by research teams composed of external observers and internal participants who jointly engage in research activities. The aim is “to co-produce basic knowledge about a complex problem or phenomenon” (van de Ven 2007, 27).
3. *Design and evaluation research* is pursued to investigate normative questions related to “the design and evaluation of policies, programs, or models for solving practical problems of a profession in question” (van de Ven 2007, 28). In addition to describing or explaining a social problem, this form of research seeks to investigate the efficacy of alternative solutions to practice problems. Evaluation researchers are usually external observers of the solutions being evaluated. External inquiry is necessary to obtain evidence-based knowledge that is both impartial and legitimate.
4. *Action/intervention research* aims to diagnose and address a problem in a specific context. Learning requires both engaging with and intervening in a specific context. In this form of research, problem solving is performed directly in the specific context “using systematic methods of data collection, feedback, reflection, and action” (van de Ven 2007, 28).

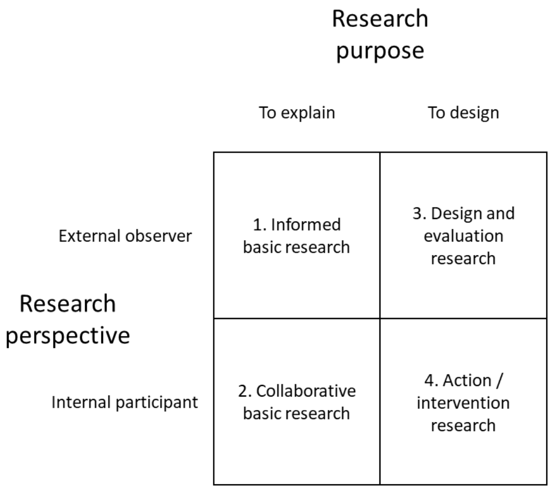


Figure 8. Research forms in engaged scholarship (van de Ven 2007, 27)

The relationship between the researcher and the practitioners plays an important role in the choice of research form. Research undertaken *for* others (e.g. design/evaluation and action research) involves an exchange relationship: Research is undertaken to solve a practitioner's problem (van de Ven 2007, 288). In these research forms, "the purpose of engagement is to ensure that the interests and values of the client are reflected in the study" (van de Ven 2007, 288). In design/evaluation research, the researcher's external perspective is necessary to determine the value of the research in achieving a predetermined objective (van de Ven 2007, 279). The research methodologies used in this research "should adhere as closely as possible to applying accepted scientific methods" (van de Ven 2007, 279), for example, case studies and field experiments. The researcher interacts with practitioners to understand the problem and to develop and evaluate a solution. In action research, it is typically required an "intensive interaction, training, and consulting by the researcher with people in the client's setting" (van de Ven 2007, 282).
In contrast, research performed *with* others (e.g. informed and collaborative research) involves a collaborative relationship (van de Ven 2007, 288). In these research forms, "the purpose of engagement is to obtain the different but complementary perspectives of collaborators for understanding the problem domain" (van de Ven 2007, 288). The level of engagement can vary. In informed basic research, engagement can range from informal meetings to formal review sessions with practitioners on each step of the research process. In collaborative basic research, engagements are typically long-lasting and take the form of participation in discussion groups and consulting engagements (van de Ven 2007, 274).

Enterprise architecture research is pursued predominately from an outside observer perspective. In fact, the three most popular research methodologies in EA are design science research, surveys, and case study research (Saint-Louis and Lapalme 2016, 79; Al-Kharusi, Miskon, and Bahari 2017). Design science research pertains to the design and evaluation research form, while the other two methodologies pertain to the informed basic research form. The empirical context of this thesis focuses on the design and evaluation research form. Manufacturing companies that are members of MADE are interested in short-time and result-oriented collaborations that could yield benefits for these enterprises. Furthermore, the fact that the author was an employee of QualiWare ApS determined his engagement with these manufacturing companies. In fact, insights in these manufacturing companies' problems were intended to be shared with QualiWare ApS. As a result, QualiWare's EA repository could be developed to address manufacturing challenges and problems. Internal participant research forms were difficult to establish in manufacturing companies due to the extensive engagement required with the companies and the reluctance of these companies to share their problems with QualiWare ApS. Furthermore, to be able to collaborate with these manufacturing companies, research needed to focus on their challenges and problems.

During the entire duration of the research conducted for this thesis, the author sought real industrial environments in which to conduct research. However, access to such environments was difficult to secure. Research was therefore often initiated in the learning factory and then used to access manufacturing companies. The initial research was used to explain the concepts included in the research to the manufacturing companies. The learning factory replicated industrial environments with a lower degree of complexity (Nardello, Madsen, and Møller 2017). Therefore, it represented a viable starting point for research. However, the differences between industrial environments and the learning factory needed to be addressed to increase the generalizability and usefulness of the research outcomes.

Following the explanation of the empirical context and the type of relationship between the author and the empirical context, this section presents the data collection approach used. Qualitative data was by far the most collected and used data in the research conducted for this thesis. When conducting research for this thesis, all of the meetings and informal conversations held in the empirical context were documented in a structured manner. These documents are field notes (Yin 2017, 125) or qualitative data files (van de Ven 2007, 218) with interview transcripts, quotes, or a description of the content of each conversation. Appendix A presents an extract from an anonymized field note. Similarly to the qualitative datum of van de Ven (2007, 218), when collecting data, interviewees were asked to describe events in detail when being interviewed. When possible, data concerning the topic being discussed was shared. This “raw data” has been codified and abstracted. For instance, a quote describing a problem at a specific company was abstracted to the relevant problem type. Some types of problem were defined before meetings, while others were defined after meetings. The qualitative data file and, in particular, the coding of data were analysed and reviewed by the supervisors. This is the data collection approach that was used to collect data and information from the empirical context. It was used to ground the research and practice problems addressed in this thesis and the articles included in it.

3.3. DESIGN AND EVALUATION RESEARCH

As presented in the previous section, the empirical context was interested in projects pertaining to the design and evaluation research form. This section explains why other types of research forms were not undertaken. It also presents research methodologies and the concepts of research relevance and rigor in research design and evaluation.

The research needed to investigate questions that could solve practice problems. QualiWare ApS was interested in supporting research on EA that would result in artefacts that would be useful for their EA repository. Manufacturing companies that were members of MADE were interested in research projects that would address their respective problems. However, they would not collaborate before being presented with a previous study explaining the artefacts and demonstrating their use. For these reasons, the learning factory was leveraged to develop and evaluate artefacts that would be used to gain access to empirical industrial contexts. On these occasions, new practice problems were discovered, and new artefacts were created based on the artefacts created in the learning factory.

Alternatively, research projects pertaining to the informed basic research form could have been undertaken. However, these projects would not have met the requirements associated with the empirical context. Although QualiWare ApS could use the outcomes of informed basic research, they were more interested in the design and evaluation of artefacts that could solve practice problems. Due to the fact that the author did not work as part of a research team, the research undertaken for this dissertation did not take the form of collaborative basic research. Research projects related to the action research form were not pursued because MADE manufacturing companies perceived the author as part of QualiWare ApS and did not permit research requiring such close engagement.

3.3.1. DESIGN AND EVALUATION RESEARCH METHODOLOGIES

Design is a problem-solving activity (Simon 1969), and design science research and design exploration are two research methodologies pertaining to the design and evaluation research form.

Design science research is based on the principle that “knowledge and understanding of a design problem and its solution are acquired in the building and application of an artifact” (Hevner et al. 2004, 82). When undertaking design science research, the guidelines from Hevner et al. (2004) and Peffers et al. (2007) were followed.

Design exploration is based on the idea that a design problem is usually ill-structured (Maher, Poon, and Boulanger 1996) and that it “involves the construction and incremental extension of problem statements and associated solutions” (Corne, Smithers, and Ross 1994). In this case, the problem space and solution space co-evolve. Exploration is defined as a phenomenon in design where the problem space interacts and evolves with the solution space over time (Maher, Poon, and Boulanger 1996).

Research in these cases must be relevant and rigorous. However, while several publications have examined how research rigor might be assessed, research relevance has not been systematically addressed on a large scale (Winter 2007, 405).

3.3.2. RESEARCH RELEVANCE

Every design science researcher states that research needs to be relevant, but few clarify what relevance is and how it can be evaluated. Hevner et al. (2004) define to research relevance as research that enables solutions to “heretofore unsolved and important business problems” (Hevner et al. 2004, 84), where “business problems and opportunities often relate to increasing revenue or decreasing cost through the design of effective business processes” (Hevner et al. 2004, 85). Frank describes relevance as “related to the value [that] a research contribution provides to business practice, mainly by helping with solving critical problems” (Winter 2007, 404). He considers “a problem as relevant, if it actually exists in practice” (Winter 2007, 404). Venable describes relevance in terms of “the topic and results should be such that they can be considered to be relevant now or they can potentially lead to relevant topics and results in the future” (Winter 2007, 408).The definitions of research relevance offered by Hevner et al., who focused on the economic impact of research to a business problem, and Frank, who focused on solving “critical” problems that exists in practice, are considered unsatisfactory. With regard to Hevner's view, economic impact is difficult to calculate when the researcher is not part of the company being investigated. With regard to Frank's view, the fact that one instance of a problem is found in a company does not guarantee that that problem is relevant. The position of Venable is which better aligns with the research conducted for this thesis. In this case, research that addressed current problems, as well as research that identified new research topics, is considered relevant.

3.3.3. RESEARCH RIGOR

This section focuses on the concept of research rigor. Research rigor requires the “application of rigorous methods in both the construction and evaluation of the designed artifact” (Hevner et al. 2004, 87).

With regard to the construction of an artefact, “rigor must be assessed with respect to the applicability and generalizability of the artefact” (Hevner et al. 2004, 88). For the construction activity, it is important that artefacts be constructed in appropriate environments alongside appropriate subject groups (Hevner et al. 2004, 88). In this thesis, the generalizability aspect of an artefact is considered to focus on the fact that an artefact is presented and demonstrated in enough detail to be replicated in other contexts. Gregor and Hevner in (2013) developed a framework on research contributions that helps in classifying contributions at different generalizability levels. Level 1 contributions are specific instantiations “in the form of products and processes” (Gregor and Hevner 2013, 341). Level 2 contributions are more general, abstract contributions “in the form of nascent design theory (e.g., constructs, design principles, models, methods, technological rules)” (Gregor and Hevner 2013, 341). Level 3 contributions are “well-developed design theories about the phenomena under study” (Gregor and Hevner 2013, 341). Design science research can produce artefacts that are at one or more of these levels.

The type and level of research contribution of a design science research project depends “on its starting points in terms of problem maturity and solution maturity” (Gregor and Hevner 2013, 344). Problem and solution maturity have either high or low values. The combination of these two values leads to four contexts and potential research contributions for a research project: invention, improvement, exaptation, and routine design.

Invention contributions entail “research in new and interesting applications where little current understanding of the problem context exists and where no effective artifacts are available as solutions" (Gregor and Hevner 2013, 346). Improvement contributions "create better solutions in the form of more efficient and effective products, processes, services, technologies, or ideas" (Gregor and Hevner 2013, 346). In a known application context, the researcher needs to develop useful solution artefacts that did not previously exist or that replace those that are suboptimal (Gregor and Hevner 2013, 346). Exaptation contributions are those "where design knowledge that already exists in one field is extended or refined so that it can be used in some new application area" (Gregor and Hevner 2013, 347). Routine design would not normally be considered research contributions but "in some cases lead to surprises and discoveries" (Gregor and Hevner 2013, 347).

Evaluation of an artefact provides the feedback required to improve the construction of future artefacts. When evaluating an artefact, its utility, quality, and efficacy must be rigorously demonstrated (Hevner et al. 2004, 83). Different types of methodologies are available for the evaluation of artefacts: (1) observational, (2) analytical, (3) experimental, (4) testing, and (5) descriptive.
Observational evaluation uses case studies to study the use of artefacts in empirical environments and field studies to monitor the use of artefacts in different empirical environments.
Analytical evaluation uses static analysis to "examine the structure of artifacts for static qualities" (Hevner et al. 2004, 86), architecture analysis to study the "fit of artifacts into technical IS architecture" (Hevner et al. 2004, 86), optimization to "demonstrate inherent optimal properties of artifact or provide optimality bounds on artifact behavior" (Hevner et al. 2004, 86), and dynamic analysis to "study the artifact in use for dynamic qualities (e.g., performance)" (Hevner et al. 2004, 86).
Experimental evaluation uses controlled experiments to "study an artifact in a controlled environment for qualities (e.g., usability)" (Hevner et al. 2004, 86), for example, field and laboratory experiments (Venable, Pries-Heje, and Baskerville 2012). Experimental evaluation also includes with which to "execute an artifact with artificial data" (Hevner et al. 2004, 86), such as computer and laboratory simulations (Venable, Pries-Heje, and Baskerville 2012). Testing uses functional testing methods to "execute artifact interfaces to discover failures and identify defects" (Hevner et al. 2004, 86) and structural testing methods to "perform coverage testing of some metric (e.g., execution paths) in the artifact implementation" (Hevner et al. 2004, 86).
Descriptive methods use informed arguments using "information from the knowledge base (e.g., relevant research) to build a convincing argument for the artifact's utility" (Hevner et al. 2004, 86) and scenarios to "construct detailed scenarios around the artifact to demonstrate its utility" (Hevner et al. 2004, 86).
Hevner et al. also list evaluation metrics for IT artefacts: "functionality, completeness, consistency, accuracy, performance, reliability, usability, fit with the organization" (Hevner et al. 2004, 85).

Although Hevner et al. (2004) present different methodologies and metrics for evaluation, they provide little guidance on how to select the most appropriate. The *strategic design science research framework* was used to guide to selection of methods and metrics for evaluating design science research (Pries-Heje, Baskerville, and Venable 2008). The framework makes three distinctions:

1. What is evaluated: the design process artefact or the design product artefact?
2. How the process artefact or product artefact is evaluated: through naturalistic or artificial forms;
3. When the evaluation occurs: ex ante or ex post construction of the artefacts.

The first distinction differentiates between whether the evaluated design artefact is a process (e.g. a method) or a product (e.g. a new IT system). Different quality metrics are used based on this distinction. The second distinction concerns whether a naturalistic evaluation context involving "*real users* using *real systems* to solve *real problems* (i.e. to accomplish a *real task* in *real settings*)" (Pries-Heje, Baskerville, and Venable 2008, 4) or an artificial evaluation context that features unreal users, systems, and/or problems is used. The latter includes simulations and field and laboratory experiments and offers advantages such as greater control, lower cost, and easier access to the empirical context. However, evaluation results obtained in artificial contexts may not be applicable to naturalistic contexts. Naturalistic evaluations guarantee more realism; they are "the real proof of the pudding" (Venable 2006). The third distinction concerns whether the evaluation occurs once the artefact is designed but not constructed and/or after an artefact is constructed. Pries-Heje et al. refer to these two moments as ex ante or ex post evaluation.

3.4. RESEARCH DESIGN GOAL AND CHOICES

This section continues the discussion of the research design by explaining the overall choices, the relationship between thesis' objectives and articles resented in subsequent chapters, the empirical context, and the framework for evaluating the research contributions of this thesis. In addition, the context and design choices are presented for each article.

The research design of each article is explained using the dimensions depicted in

Table 1. For each objective, *background knowledge* refers to the body of knowledge used to analyse the empirical context and research to find problems. *Research problem* relates to the research gap, meaning the problem found in research. *Practice problem* is associated with the problem identified in the empirical context. *Empirical context* describes the collaborations and environment available at the time the article was written. *Research question* identifies the direction of the investigation pursued to address the research and practice problems. *Empirical observations* relate to observations made in the empirical context. *New background knowledge* refers to research that was found to be relevant to the research question. Finally, *research*

methodology specifies research methodology applied to address the research questions.

Table 1. Meta-overview of the research design of each article.

Dimensions	Article 1	Article 2-3	Article 4	Article 5	Article 6
Background knowledge	Smart products and digital manufacturing Learning Factory	Reference architecture models for digital manufacturing, learning factory and EA models	EA modelling, Process Models, Process Mining	Method from article 4 Automated EA modelling Production platform Production Process Classification	Method from article 5
Research problem	Lack of description of empirical environments to research digital manufacturing	What is RAMI4.0 and how it can be instantiated?	EA modelling process is inefficient and time consuming (Holm et al. 2014; Hauder, Matthes, and Roth 2012; Buschle et al. 2012; Hauder et al. 2013)	Lack of automated EA modelling methods for the business aspect. Data too detailed. Superficial explanation of automated EA modelling methods.	Automated EA modelling methods do not support managing process and data heterogeneity
Practice problem	Lack of understanding the Industry 4.0 transformation and digital manufacturing	Lack of access to data and information about the learning factory Problematic to share information about the learning factory among students and researchers	Lack of overview of manufacturing processes and the equipment used to support these processes Lack of informaiton standardization	Efficiently manage business data. Understand data and extracting value from it.	Process and data heterogeneity
Empirical context	Learning factory MADE manufacturing companies	QualiWare ApS Learning factory MADE manufacturing companies	QualiWare ApS Learning factory Enterprise A Swedish manufacturing company	The ones of article 4 and a Swedish integration platform	QualiWare ApS Enterprise B and C

Table 1. Meta-overview of the research design of each article (continued).

Dimensions	**Article 1**	**Article 2-3**	**Article 4**	**Article 5**	**Article 6**
Research question	What components are required in a learning factory in order to conduct research on digital manufacturing? How are research and education on digital manufacturing conducted in a learning factory?	Which EA models instantiate RAMI4.0? How does an instantiation of RAMI4.0 with EA models contribute to organizational learning? How does an instantiation of RAMI4.0 with EA models contribute to the information dissemination sub-process? How are EA models for digital manufacturing enhanced to include manufacturing documentation? How are EA models for digital manufacturing enhanced to include data about the status of	How to include abstraction in a new automated EA modelling method? What are the challenges associated with introducing abstraction in a new automated EA modelling method?	What components are necessary in an automated EA modelling method that abstracts data to EA models related to the business aspect?	How to further develop automated EA modelling methods that model business aspects to address with process heterogeneity? How to further develop automated EA modelling methods that model business aspects to include documentation in EA models? How to further develop automated EA modelling methods that model business aspects to include performance measurements in EA models?
Empirical observations	Did not find industrial partners developing digital manufacturing components. Observation of the learning factory: goals, components, users.	Learning factory: smart products, MES Interviewes with learning factory manager	The ones of articles 2 and 3 and one interview at Enterprise A and one at the Swedish manufacturing company	Learning factory: smart products, MES, SAP ERP Interview with learning factory manager 5 meetings at Enterprise A One meeting at a Swedish integration platform	1 meeting at Enterprise B and 3 meetings at Enterprise C
New background knowledge	N/A	Organizational learning	Automated EA modelling Production platform Production Process Classification	Abstraction in Enterprise Architecture Modeling	Heterogeneities in international manufacturing companies
Research methodology	N/A	Design science (Hevner et al. 2004; Peffers et al. 2007)	Design science (Hevner et al. 2004; Peffers et al. 2007)	Design exploration (Corne, Smithers, and Ross 1994; Maher, Poon, and Boulanger 1996)	Design exploration (Corne, Smithers, and Ross 1994; Maher, Poon, and Boulanger 1996)

3.4.1. OVERALL THESIS OBJECTIVE

The research gaps identified in Chapter 2 and the empirical context of this thesis led to the formulation of the following overall research questions:

> Which EA models can be used as digital models for digital manufacturing?
>
> How are EA models created and enhanced with data and information from different enterprise information systems?

To address these research questions, three thesis objectives were defined. As shown in Figure 9, the six articles included in this thesis contributed towards achieving these objectives.

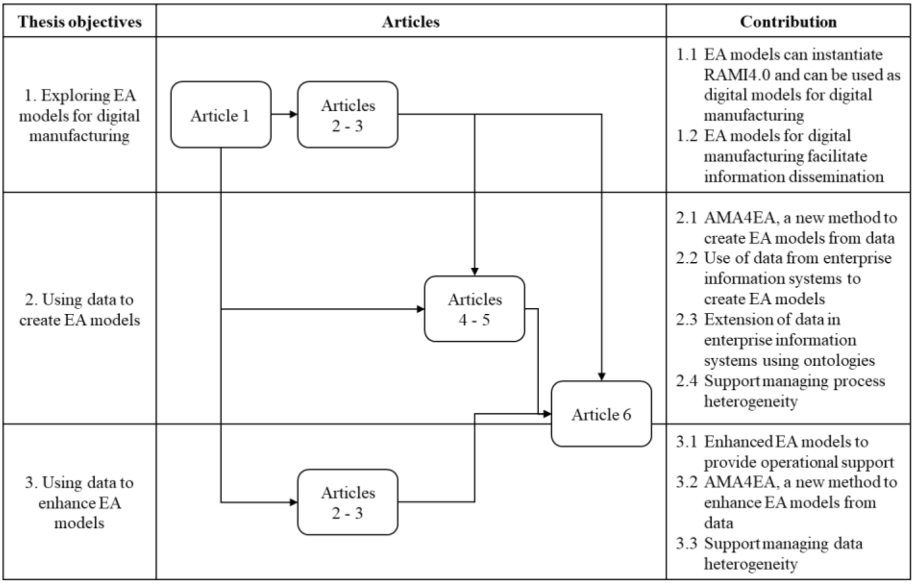


Figure 9. Relationship between thesis objectives and articles, and between articles

Figure 10 presents the timeline of the research conducted for this thesis including the articles, the author's stay abroad, and the most important field notes.

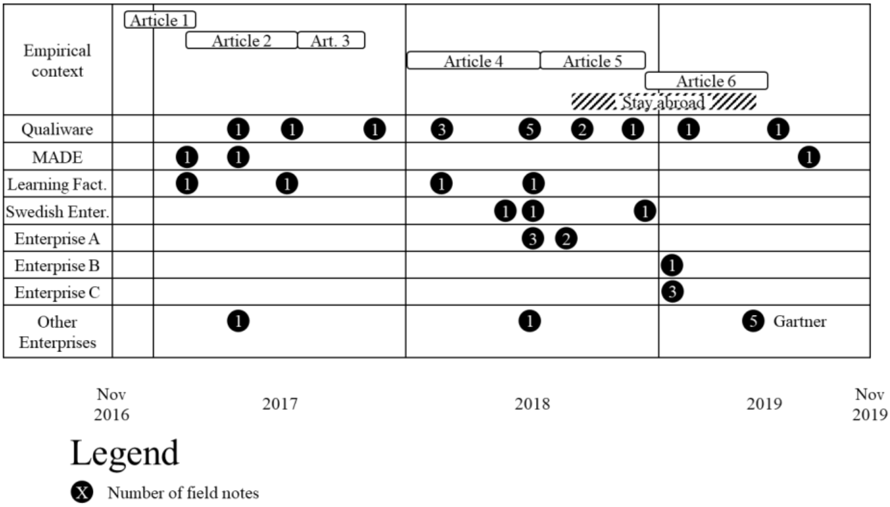


Figure 10. Research timeline.

As shown in Figure 10, the empirical observations were largely based on the author's interactions with four enterprises. The Swedish enterprise supplies cutting tools and services to the metal cutting industry. It is a large international manufacturing company with production sites around the world. The Swedish integration platform is a spin-off of this enterprise. Both were present at the meetings, and therefore they are represented together in Figure 10. Enterprise A is a large Danish manufacturer of discrete products with mechanical, electrical, and software components. Enterprises B and C are large companies of engineer to order products.

Based on the discussion in Section 3.3.3, Table 2 defines the evaluation framework used for each objective.

Table 2. Framework for evaluating the research contributions of this thesis.

Thesis Objective	Design Process or Design Product	Contribution Type	Generalizability Level	Naturalistic or Artificial	Ex Ante or Ex Post	Criteria
1. Exploring EA models as digital models for digital manufacturing	Process	Routine design	N/A	N/A	N/A	N/A
	Product	Exaptation	Level 1 and 2	Naturalistic	Both	Feasibility, Usefulness and Applicability
2. Using data to create EA models for digital manufacturing	Process	Improvement	Level 1 and 2	Naturalistic	Both	Usefulness, Usability and Efficiency
	Product	Routine design	N/A	N/A	N/A	N/A
3. Using data to enhance EA models for digital manufacturing	Process	Improvement	Level 1 and 2	Naturalistic	Both	Usefulness, Usability and Efficiency
	Product	Routine design	N/A	N/A	N/A	N/A

Design process artefact or design product artefact

For each objective, the goal was to develop either a design process artefact, a design product artefact, or both (Pries-Heje, Baskerville, and Venable 2008). For the first objective, which concerns the use of EA models as digital models for digital manufacturing, the focus is on a design product artefact. It was considered important to identify, apply, and extend known EA models to determine whether they can be used as digital models for digital manufacturing. The method used to develop the EA models is yet to be described, but it is not expected to be a research contribution. For the second objective, which concerns using data to create EA models for digital manufacturing, the aim was primarily to make a contribution in the form of a design process artefact. In this case, a contribution to automated EA modelling methods to model business aspects was expected. For the third objective, which concerns using data to enhance EA models for digital manufacturing, the focus is also on producing a design process artefact. The aim is to improve automated EA modelling methods by expanding them to include data and information and to thus enhance EA models.

Contribution type

This aspect is based on the four contribution types presented by Gregor and Hevner (2013). The first objective focuses on the design product artefact. It is expected to be an exaptation contribution focused on the possibility of using EA models, a well-known solution, as digital models for digital manufacturing, a new application area for EA models. The second objective focuses on the design process artefact. The artefact is expected to be an improvement contribution addressing how existing automated EA modelling methods can be improved to create EA models related to the business aspect. Enterprise architecture models as design product artefacts could be an area of contribution, though they are not the focus of this objective. Similarly, the third objective also focuses on producing a design process artefact intended to improve automated EA modelling methods. Contributions to EA models, a design product artefact, could also lead to a research contribution although it is not the priority for this objective.

Generalizability level

There are three levels of research generalizability (Gregor and Hevner 2013). With each objective's respective artefact, the aim is to produce research that contributes to generalizability level 1 and 2 (Gregor and Hevner 2013). Level 1 contributions (i.e. specific instantiations) are important because they support the author’s interaction with the empirical context and lay the foundations for level 2 contributions. Level 2 contributions (i.e. those that are more abstract) are significantly more valuable contributions to research. For the artefact that is not in focus (i.e. design process artefact or design product artefact with routine design as contribution type), there is no target level of generalizability because no contribution is expected.

Naturalistic or artificial

There are naturalistic and artificial evaluation contexts (Pries-Heje, Baskerville, and Venable 2008, 4). Ideally, all research contributions will be evaluated in naturalistic contexts, as such evaluations ensure greater realism and are “the real proof of the pudding” (Venable 2006). Evaluations in artificial contexts are possible, but they are not the first choice.

Ex ante or ex post

Ideally, evaluation should occur both ex ante, to evaluate the design of the artefact, and ex post, to evaluate the artefact itself.

Criteria

The fourth aspect is the criteria or metrics used for the evaluation of each contribution type. These criteria are summarized in Table 2. For exaptation research contributions, the most important evaluation criteria are feasibility, usefulness, and applicability. Feasibility involves determining whether it was feasible to design and/or construct the artefact. Usefulness involves determining the degree to which the artefact was useful in terms of achieving the predetermined purpose. Applicability involves determining the degree to which the artefact can be applied in different contexts. For improvement research contributions, the most important evaluation criteria are usefulness, usability, and efficiency. Usability evaluates the degree to which the person involved in the evaluation was able to use the artefact. Efficiency evaluates the difference in terms of the resources (e.g. time or man hours) needed by the new artefact compared to those required by what is being improved.

3.4.2. EXPLORING EA MODELS FOR DIGITAL MANUFACTURING

This section presents the research design choices related to the first objective. It starts by summarizing the research gaps, challenges, and problems that exist in the empirical context. It then describes the design of the articles related to this objective.

As discussed in Section 1.3, EA models are of primary importance for an enterprise because they make it possible to analyse the real world by focusing on certain aspects; in addition, they can guide the development and implementation of an enterprise information systems. Enterprise architecture models establish a relationship between an enterprise and the real world based on that company’s enterprise information systems and data. As discussed in Section 1.4, exploring the use of EA models as digital models for digital manufacturing requires addressing the information availability challenge in manufacturing companies. As mentioned in Section 1.2, this challenge relates to a difficulty in accessing information stored on enterprise information systems (e.g. few employees know how to find and extract information) and a lack of understanding of an enterprise's resources and processes (e.g. no models describing the processes and equipment of the manufacturing functional unit are shared with the R&D unit).

Due to the challenge identified above, enterprises operating in the empirical context noted the problem that they collect large amounts of data from smart products and manufacturing processes but experience difficulties in disseminating and using it internally. Reference architecture models are being developed to guide the modelling of digital manufacturing, but their application to address this problem is not yet clear.

The MADE manufacturing companies and QualiWare ApS are interested in research that supports practitioners working in enterprises that are attempting to understand and shift towards digital manufacturing. However, MADE manufacturing companies were reluctant to allow projects to be conducted within their companies. For this reason, the research initiatives conducted for this thesis often leveraged the learning factory as a “test bed”. Due to the learning factory’s role, the first article describes the learning factory. The companies’ interest in applied research also influenced the research questions formulated to address the first objective, which are as follows:

> Which EA models instantiate reference architecture models for digital manufacturing?
>
> How do EA models for digital manufacturing facilitate access to information about digital manufacturing?
>
> How are EA models for digital manufacturing improving the understanding of processes and resources in digital manufacturing?

These research questions are addressed in articles 2 and 3.

Article 1

The first article is titled “The Smart Production Laboratory: A Learning Factory for Industry 4.0 Concepts” (Nardello, Madsen, and Møller 2017). Its research design is summarized in

Table 1. This article was useful in establishing a foundation for the empirical context of the other articles presented in this thesis. The first months of the research conducted for this thesis were focused on understanding manufacturing and production lines, as well as smart products, the Industry 4.0 transformation, and digital manufacturing. Previous research on these topics was very limited. The main sources explaining digital manufacturing stemmed from practice (e.g. consulting companies, technology providers, and pioneering manufacturing companies). The goal was to better understand digital manufacturing and its implications for researchers and practitioners. More specifically, there was a lack of a description of environments that could be used to research digital manufacturing. During the interactions with the manufacturing companies that are members of MADE, practitioners’ problems in understanding digital manufacturing and its implications were acknowledged. The learning factory at Aalborg University was inaugurated few months prior to the beginning of the research conducted for this thesis. The author had the opportunity to

access it and interact with the learning factory manager and professors who were developing it. Given the empirical context and the identified research and practice problems, the following research questions were deemed intriguing to investigate:

> What components are required in a learning factory in order to conduct research on digital manufacturing?
>
> How are research and education on digital manufacturing conducted in a learning factory?

Driven by curiosity and the need to explain the elements in a learning factory for digital manufacturing and how research is conducted in such an environment, the author examined the learning factory. No precise research methodology was applied. The research questions were addressed through providing a description of the empirical context. The contributions of this article are a description of the learning factory components for digital manufacturing and a presentation of the research and education initiatives that can be pursued in such a context. This article was useful in establishing a foundation for the empirical context of the other articles.

Articles 2 and 3

Two articles were written to address the research questions associated with the first objective. The first was a conference proceeding titled “The Industry 4.0 Journey: Start the Learning Journey with the Reference Architecture Model Industry 4.0” (Nardello, Møller, and Gøtze 2017b). The second was a journal article extending the conference proceeding titled “Organizational Learning Supported by Reference Architecture Models: Industry 4.0 Laboratory Study” (Nardello, Møller, and Gøtze 2017a). Since article 3 was an extension of article 2, for the concerns of the research design, they are discussed together. Their research design is summarized in

Table 1. The starting points for the research conducted for these articles were reference architecture models for digital manufacturing, the learning factory, and EA models. Reference architecture models are an important starting point for modelling digital manufacturing because they define the key aspects to be modelled in and the structure of EA models. The difficulty in accessing manufacturing companies resulted in the choice to use the learning factory at Aalborg University, as it offered a controlled environment with industrial equipment. Finally, knowledge concerning EA models and their core elements was also important as a starting point in terms of exploring how reality could be modelled.

The empirical context was represented by QualiWare ApS, the learning factory, and MADE manufacturing companies. Qualiware ApS followed the development of RAMI4.0. They were interested in applying this standard to gain a better understanding of digital manufacturing and how their EA repository could be used for digital manufacturing. With regard to the learning factory, the author interviewed its manager to identify the challenges encountered in the factory.

Two main problems related to the first thesis objective emerged: The first was a lack of access to data and information concerning the learning factory. Learning factory data is only accessible within the learning factory through accessing its manufacturing execution system (MES). Furthermore, it was difficult to find specific information on the system and its database. The second problem related to the fact that there were no models for presenting the processes and resources in the learning factory to new students and researchers. These problems were also mentioned by the MADE manufacturing companies. It emerged that some of the companies interviewed had experienced problems accessing data in their manufacturing enterprise information systems. Furthermore, when presented with the problems identified in the learning factory, they could relate to them and confirmed that these problems also occurred in their companies.

Given these problems and the empirical context, different research forms could have been pursued. Conducting informed basic research could have led to an analysis of the concepts included in the reference architectural models and the models required to instantiate them. In addition, differences between the various reference architectural models and among EA models could have been identified. By conducting design and evaluation research, it is possible to apply the reference architecture models in an empirical context. Independently from the research form, different sources for EA models could have been used: academic sources (Winter and Fischer 2007; Lankhorst et al. 2017), and/or practitioner sources such as QualiWare ApS. In the case of a design and evaluation form, several EA repositories could have been applied and compared to when instantiating the reference architecture models with EA models. The empirical context influenced the research design by providing a clear direction, as QualiWare ApS and the MADE manufacturing companies were more interested in design and evaluation research. Furthermore, QualiWare ApS expressed particular interest in instantiating RAMI4.0 to understand how their EA repository supports it. This promoted the use of QualiWare’s EA repository and EA models over other alternatives.

To address and frame the investigated problems, background knowledge on organizational learning was used. Organizational learning is “the process by which new knowledge or insights are developed by a firm” (Tippins and Sohi 2003, 749). In particular, the information dissemination sub-process was considered very relevant to the problems being addressed. To address the research and practice problems and satisfy the requirements of QualiWare ApS and the MADE manufacturing companies, the following research questions were investigated:

> Which EA models instantiate RAMI4.0?
>
> How does an instantiation of RAMI4.0 with EA models contribute to organizational learning?

> How does an instantiation of RAMI4.0 with EA models contribute to the information dissemination sub-process?

To address these research questions, the learning factory and its MES were analysed, and the learning factory manager was interviewed. The research conducted for this thesis focused on the design science research methodology (Hevner et al. 2004; Peffers et al. 2007) for the following reasons: it involved the design of artefacts, and it included empirical observations intended to help the author to understand the problem and to evaluate the contribution of the artefacts in terms of addressing the problem in the empirical context being investigated.

The findings of this research are expected to be difficult to generalize since the instantiation at the learning factory is simpler than in industrial environments. Therefore, the contributions of this research should be further developed and tested in multiple industrial environments to render them more generalizable.

3.4.3. USING DATA TO CREATE EA MODELS FOR DIGITAL MANUFACTURING

The second objective of this thesis is to investigate the use of data to create EA models. As presented in Section 2.2, EA models for digital manufacturing represent products, processes, components, and resources. Digital manufacturing involves the application of data and information to enhance manufacturing. Therefore, EA models for digital manufacturing could be created from data to facilitate the understanding of manufacturing data and support a company's shift towards digital manufacturing.

The author intensively engaged with the empirical context. This resulted in interviews being conducted at QualiWare ApS, the learning factory, two MADE manufacturing companies, a Swedish manufacturing company, and a Swedish integration platform. These interviews led to the identification of several practice problems; these problems in turn guided the search for state-of-the-art solutions intended to address them. As for the previous objective, MADE manufacturing companies and QualiWare ApS supported research that could address practice problems. The need, in both practice and research, was to develop more efficient approaches for creating EA models. This led to the definition of the following research question:

> How are EA models for digital manufacturing created from the data stored enterprise information systems?

Articles 4, 5, and 6 investigate this research question and build on one another. Each article addresses problems that lead to the identification of new problems, which are addressed in the following article. Article 4 investigates the inclusion of abstraction in a novel automated EA modelling method and the challenges related to the method. Article 5 uses this work to develop a general-purpose solution that can model business aspects. In addition, it identifies the components of this general-purpose solution. Article 6 develops the solution further to address process and data heterogeneity.

Article 4

The first article written to address the objective concerning the use of data to create EA models is titled "Process Model Automation For Industry 4.0: Challenges For Automated Model Generation Based On Laboratory Experiments" (Nardello, Møller, and Gøtze 2018). Its research design is summarized in

Table 1. The relevant background knowledge for this article revolved around three main objectives. Enterprise architecture modelling is the process used to create EA models (Lankhorst et al. 2017, 145). Process models are EA models fundamental for the design, implementation, management and control of processes (Van Der Aalst 2016). The process mining technique called process discovery uses event logs to create a process model (Van Der Aalst 2016). During the development of the EA models for the instantiation of RAMI4.0 in the previous articles, the author realized that the EA modelling process is inefficient and time consuming. Research also recognized these problems in EA modelling (Holm et al. 2014; Hauder, Matthes, and Roth 2012; Buschle et al. 2012; Hauder et al. 2013). Several manufacturing companies were contacted to discuss the problem of creating EA models. A large Danish manufacturing company that is a member of MADE and one large Swedish manufacturing company agreed to collaborate. During the meetings held with these companies, production managers raised the problem of not having an overview of their manufacturing processes and the equipment used to support these processes. As presented in Section 1.2, this problem is related to the lack of information standardization, which limits information availability in an enterprise. The author suggested that he could investigate how high-level production process models with an efficient modelling approach could be created. The companies confirmed that this type of research would be relevant in terms of addressing their problems.

This research could not be performed autonomously. Alignment with the empirical context was required to conduct research that would create EA models using data. First, a common interested between QualiWare ApS and the author was identified. They were interested in the integration of QualiWare' EA repository with SAP enterprise resource planning (ERP), and, to investigate this integration, they would provide the software developers needed to implement the algorithms required for the solution. The learning factory uses SAP ERP and for this reason was included in the research work. Therefore, the empirical context for researching the creation of EA models based on SAP ERP data was established.

Before the author attempted to develop a solution, he decided to acquire new background knowledge as starting point for this research. Automated EA modelling methods and process mining research was investigated to identify the state-of-the-art EA solutions that could be applied to address the problem. The concept of a production platform was also identified as useful for addressing the problem. A production platform is a solution intended to standardize production assets by mapping “products with corresponding production systems and developing both simultaneously” (Sorensen, Brunoe, and Nielsen 2018). This mapping also involves production processes, and it classifies production processes to standardize processes.

To address the research and practice problems and the empirical context, it was necessary to conduct research pertaining to the design and evaluation research form. After an analysis of the state-of-the-art in automated EA modelling, the limitations of existing contributions to abstracting data to create EA models were identified. Therefore, the following research questions were investigated:

> How to include abstraction in a new automated EA modelling method?
>
> What are the challenges associated with introducing abstraction in a new automated EA modelling method?

Given that the research form of this article is similar to the research form of previous articles, the design science research methodology was applied (Hevner et al. 2004; Peffers et al. 2007).

For the development of an initial solution to the problem of abstraction in automated EA modelling methods, the learning factory and its ERP and MES enterprise information systems were used. Furthermore, several interviews with learning factory manager were conducted to develop an understanding of the data stored on the ERP and MES as well as to evaluate the solution. However, the level of commitment required from the manufacturing companies exceeded what they could provide for the development of the first solution.

The purpose of this article was to explore how automated EA modelling methods could be improved to include abstraction as well as to identify the challenges related to this inclusion.

Article 5

The previous conference article was used as starting point for the journal article titled “Automated Modeling with Abstraction for Enterprise Architecture (AMA4EA): Business Process Model Automation in an Industry 4.0” (Nardello et al. 2019a). Its research design is summarized in

Table 1. The background knowledge is the same as that considered in article 4: process models, process mining, EA modelling, automated EA modelling, production platform, and production process classification. This article also used the new modelling method. In addition, it further investigated the research problem addressed in article 4. It focused on three main problems: The first one was the limitation of automated EA modelling methods in creating EA models related to business aspects.

Indeed, the fact that these methods could not adequately cover business aspects made automated EA modelling unsuitable for managing business data. The second problem was that data from enterprise information systems is too detailed for creating EA models (Hauder, Matthes, and Roth 2012; Farwick et al. 2016). Finally, the third problem was the authors of the articles superficial explanation of automated EA modelling methods, which inhibits researchers and practitioners from implementing them. These methods are, however, very useful in applying a uniform structural metadata to business data. The application of these methods to business data is expected to increase due to the amount of data that will likely be managed by future enterprise information systems with smart products.

To understand the practice problems related to these research problems, the author and his supervisors interacted with and analysed several manufacturing companies. The author held five meetings with the following stakeholders in a large MADE-affiliated manufacturing company: (1) four production managers, (2) one manager from the system reference architecture cross-functional team, (3) one manager of the product disassembly process, (4) several managers part of the data management team, and (5) one manager from sales and operations planning. Furthermore, the author and his supervisors engaged with Ghost Nodes (an integration platform) and a large Swedish manufacturing company.

The practice problem that emerged from these meetings is that these companies were replacing many legacy systems (e.g. three MESs) with a new enterprise information system (e.g. one MES) to collect more business data from production processes. Their problem is to be able to manage data which is related to the core business of an enterprise (e.g. production process). The companies explained that gathering large amounts of such business data is not challenging. What is problematic, however, is understanding the data and extracting value from it. In fact, the data gathered is too detailed and too complex to be understood by these companies' management. Despite the extensive efforts made to secure access to industrial business data, none of the companies shared their data. As a result, the same empirical context as that of the previous article was used. However, this article used as its starting point the contribution of the previous one, and it aimed to address the new research and practice problems. To do so, the following research question was investigated:

> What components are necessary in an automated EA modelling method that abstracts data to EA models related to the business aspect?

As for the previous article, the observations made in the empirical context focused on the learning factory, its enterprise information system, and its manager. To address the abstraction problem associated with automated EA modelling methods, new background knowledge on abstraction in enterprise architecture modelling was included in this article. Design exploration was adopted as a research methodology (Corne, Smithers, and Ross 1994; Maher, Poon, and Boulanger 1996).

Article 6

The automated modelling with abstraction for EA (AMA4EA) method presented in the previous article was extended in another journal article entitled "Incorporating Process and Data Heterogeneity in Enterprise Architecture: Extended AMA4EA in an International Manufacturing Company" (Nardello et al. 2019b). Its research design is summarized in

Table 1. This article contributes to the use of data to both create and enhance EA models. The background knowledge considered is the same as for previous article. The research problem is that international manufacturing companies have production sites that operate in heterogeneous environments (Ghoshal and Nahria 1989). These sites different environments result from different environmental and historical conditions (Ghoshal and Nahria 1989). As a result, processes and enterprise information systems differ across subsidiaries. These "different processes, IT systems, environmental and historical conditions lead to the problem of process and data heterogeneity" (Nardello et al. 2019b, 7). These manufacturing companies thus find comparing their production processes to achieve process efficiency problematic. This problem was also investigated in practice. The author and his supervisor contacted more than 10 companies to request access to their ERP data. Although several showed interest in collaborating, only two large manufacturing companies shared their data and allocated time for meetings. For the first company, the author held three meetings with the following stakeholders: (1) a researcher on virtual reality, in order to understand the production processes at the company and the models they currently use; (2) the head of business development; and (3) the product engineer, production lead, and technical designer. Based on these meetings, it was determined that production process models are created manually during the product design phase but are not kept aligned with the data stored on the ERP during production. The company confidentially shared the production routings of three similar components from the ERP. In the other manufacturing company, the author held one meeting, which was attended by a production manager, a production engineer, a system administrator of the ERP and MES, and the head of business intelligence. The main outcome of the meeting was that the production processes used to manufacture the same component are extremely heterogenous across plants. In the ERP system, one process analysed consisted of 26 sub-processes, while, in another production site, it was structured in more than 200 sub-processes.

To address the research and practice problems, the following research question was investigated:

> How to further develop automated EA modelling methods that model business aspects to address with process heterogeneity?

To address better understand the research and practice problems, new background knowledge on process heterogeneity in international manufacturing companies was included (Ghoshal and Nahria 1989; Netland 2013; Netland and Aspelund 2014). Design exploration was employed as a research methodology (Corne, Smithers, and Ross 1994; Maher, Poon, and Boulanger 1996).

Upon reflecting on the data provided by the two companies, it was found that they could have been compared. The decision to go with only the data from enterprise B was largely due to a desire to focus on the development of a solution rather than focusing on analysing the problem. Exploring two potential solutions in detail was not possible within the timeframe available for this research; it was only possible to write one journal article in the time available. However, reflections on using the data from the other company are included in Chapter 6.

3.4.4. USING DATA TO ENHANCE EA MODELS FOR DIGITAL MANUFACTURING

The third objective of this thesis is to investigate the use of data to enhance EA models used for digital manufacturing to allow them to provide operational support. To provide operational support, it was necessary to include additional data and information beyond that used to create the EA models. By including additional data and information, EA models can provide operational support for enhancing manufacturing products and processes. As presented in Section 2.3, this objective also relates to the data heterogeneity challenge, as the data to be included in the EA models is stored inconsistently across different enterprise information systems. Inspired by the process enhancement technique of process mining, this objective aims at including data and information (e.g. performance measurements from manufacturing processes and assembly documentation, which could be used to structure information dissemination) in EA models.

The author thoroughly engaged with the empirical context, which, in this case, was the learning factory, QualiWare ApS, and two MADE manufacturing companies. This led to the identification of new practice problems that had been partially addressed by existing research. As before, the research was designed to address the needs of both practitioners and researchers. This led to the definition of the following research question:

> How are EA models for digital manufacturing enhanced using additional data and information stored on different enterprise information systems?

Articles 2 and 3 focused on the design product, namely the EA models for digital manufacturing. Article 6 focused on the design process, namely the use of the automated EA modelling method to enhance EA models. The research design of the articles was previously explained in Sections 3.4.2 and 3.4.3. Based on the previous explanation of the design choices related to the first and second objectives, the additional considerations in each article related to this specific thesis objective are presented below.

Articles 2 and 3

Articles 2 and 3 address the problem that the EA models do not include documentation and information concerning the status of the production line. Documentation was stored on different systems, and the students and the researchers only became aware of the existence of such documentation as a result of attending meetings. Therefore, articles 2 and 3 investigated the following research questions:

> How are EA models for digital manufacturing enhanced to include manufacturing documentation?
>
> How are EA models for digital manufacturing enhanced to include data about the status of manufacturing products and processes?

The empirical context was QualiWare ApS, the learning factory, and the MADE manufacturing companies. Qualiware ApS was interested in understanding how their EA repository could be used to include additional documentation and data in EA models for digital manufacturing. The interview with the manager of the learning factory led to the identification of the challenges mentioned above.

Article 6

Article 6 investigated how the solution discussed in article 5 could be further developed to include performance measurements and documentation in EA models in contexts characterized by process and data heterogeneity. The research design of article 6 was presented above, and the research questions related to this objective are as follows:

> How to further develop automated EA modelling methods that model business aspects to include documentation in EA models?
>
> How to further develop automated EA modelling methods that model business aspects to include performance measurements in EA models?

3.5. SUMMARY OF RESEARCH QUESTIONS

The transformation to digital manufacturing revolves around the application of data and information to enhance manufacturing and requires digital models, feedback loops, and integration. Data is a core part of digital manufacturing and the Industry 4.0 transformation. Examples of such data include that from smart products, data in digital models, and data in feedback loops. Enterprise architecture can support enterprises in managing data. The overall research questions of the thesis are as follows:

> Which EA models can be used as digital models for digital manufacturing?

> How are EA models created and enhanced with data and information from different enterprise information systems?

To address these questions, three thesis objectives were defined.

3.5.1. EXPLORING EA MODELS FOR DIGITAL MANUFACTURING

The first objective concerned the exploration of the use of EA models for digital manufacturing. Reference architecture models for modelling digital manufacturing are being developed, and, in order to evaluate them appropriately, it is important to apply them. Enterprise architecture models and reference architecture models can be instantiated through the development of artefacts to address practice problems. The research questions for this thesis objective were as follows:

> Which EA models instantiate reference architecture models for digital manufacturing?

> How do EA models for digital manufacturing facilitate the dissemination of information about digital manufacturing?

> How are EA models for digital manufacturing improving the understanding of processes and resources in digital manufacturing?

An attempt was made to identify an industrial context that could be described and analysed to address these questions was searched. However, the failure to identify such a context resulted in the decision to use the learning factory to develop the EA models required to describe and analyse the research questions. The research related to this objective was structured in the form of three articles.

Article 1

The first article focused on the description of the empirical context. It investigated the following research questions:

> What components are required in a learning factory in order to conduct research on digital manufacturing?

> How are research and education on digital manufacturing conducted in a learning factory?

To address these research questions, a descriptive study was undertaken.

Articles 2 and 3

The second and third articles focused on the design and evaluation of the artefacts with which to develop EA models for digital manufacturing. In articles 2 and 3, the research questions for the first objective were further specified to fit the requirements and problems associated with the empirical context:

> Which EA models instantiate RAMI4.0?
>
> How does an instantiation of RAMI4.0 with EA models contribute to organizational learning?
>
> How does an instantiation of RAMI4.0 with EA models contribute to the information dissemination sub-process?

These questions were addressed through the application of the design science research methodology. Empirical observations were used to group the problems in practice problems, and artefacts intended to address these problems were developed and evaluated.

3.5.2. USING DATA TO CREATE EA MODELS FOR DIGITAL MANUFACTURING

The second objective was to research the use of data to create EA models for digital manufacturing. Digital manufacturing involves the application of data and information to enhance manufacturing. Enterprise architecture can support enterprises in managing the growing volume and complexity of data. The research question for the second objective, which concerned using data to create EA models, was as follows:

> How are EA models for digital manufacturing created from the data stored enterprise information systems?

This research question was addressed in three separate articles.

Article 4

Article 4 focused on the problems of automated EA methods related to abstraction. The following two research questions were formulated to address research and practice problems:

> How to include abstraction in a new automated EA modelling method?
>
> What are the challenges associated with introducing abstraction in a new automated EA modelling method?

To address these questions, an artefact in the form of a new modelling method, was designed. The artefact was then evaluated in the empirical context in which it was developed, and new challenges were identified.

Article 5

Article 5 further continued the work presented in the previous article. It improved the existing artefact by developing a new automated EA modelling method. This article focused on the following question:

> What components are necessary in an automated EA modelling method that abstracts data to EA models related to the business aspect?

The components of the new modelling method developed in article 4 were revised and clarified. This led to a new automated EA modelling method that was in line with the previous version.

Article 6

Following the application of the method in certain MADE manufacturing companies, the sixth article addressed new research and practice problems. Based on the new empirical observations and data from practitioner, the following research question was investigated:

> How to further develop automated EA modelling methods that model business aspects to address with process heterogeneity?

3.5.3. USING DATA TO ENHANCE EA MODELS FOR DIGITAL MANUFACTURING

The third objective of this thesis is to investigate the use of data to enhance EA models used for digital manufacturing to allow them to provide operational support. To provide such support, it was necessary to include data and information beyond that used in the creation of EA models. This need led to the following research question:

> How are EA models for digital manufacturing enhanced using additional data and information stored on different enterprise information systems?

Articles 2 and 3

Articles 2 and 3 investigated the following research questions:

> How are EA models for digital manufacturing enhanced to include manufacturing documentation?

> How are EA models for digital manufacturing enhanced to include data about the status of manufacturing products and processes?

Article 6

Article 6 investigated the following research questions:

> How to further develop automated EA modelling methods that model business aspects to include documentation in EA models?

> How to further develop automated EA modelling methods that model business aspects to include performance measurements in EA models?

To address these research questions, new artefacts were developed. This led to the extension of the automated EA modelling method presented in article 5.

The contributions of each article towards this thesis' objectives are presented in Chapters 4, 5, and 6, respectively. Chapter 7 synthesizes these contributions. In Chapter 8, the research rigor of the research contributions of this thesis is evaluated using the framework presented in Table 2. In addition, Chapter 8 discusses the importance for research and the implications for practice of the contributions presented in Figure 7.

CHAPTER 4. EXPLORING EA MODELS FOR DIGITAL MANUFACTURING

This chapter presents the research related to the first thesis objective. Articles 1, 2, and 3 are summarized by presenting their respective research questions and content. Article 1 focuses on the learning factory, whereas articles 2 and 3 address the instantiation of RAMI4.0 through EA models. Thereafter, additional insights from and reflections on the articles are presented. Finally, the contributions of the articles are summarized to address the research questions at the level of this thesis' objectives. This summary is then synthesized in Chapter 7.

This chapter presents the articles relevant to the following research questions:

> Which EA models instantiate reference architecture models for digital manufacturing?
>
> How do EA models for digital manufacturing facilitate the dissemination of information about digital manufacturing?
>
> How are EA models for digital manufacturing improving the understanding of processes and resources in digital manufacturing?

The managers from the MADE manufacturing companies were very interested in reference architecture models for digital manufacturing and were sought guidance on how to instantiate and use them. QualiWare ApS had early access to RAMI4.0 and was interested in investigating the instantiation of this reference architecture model through their EA repository. The author searched for other instantiations, both in research and practice, without finding significant contributions. Therefore, the learning factory was used to investigate the instantiation of RAMI4.0.

Article 1 focused on the explanation of the learning factory as an empirical context for digital manufacturing. Articles 2 and 3 focused on the design and evaluation of EA models as digital models for digital manufacturing.

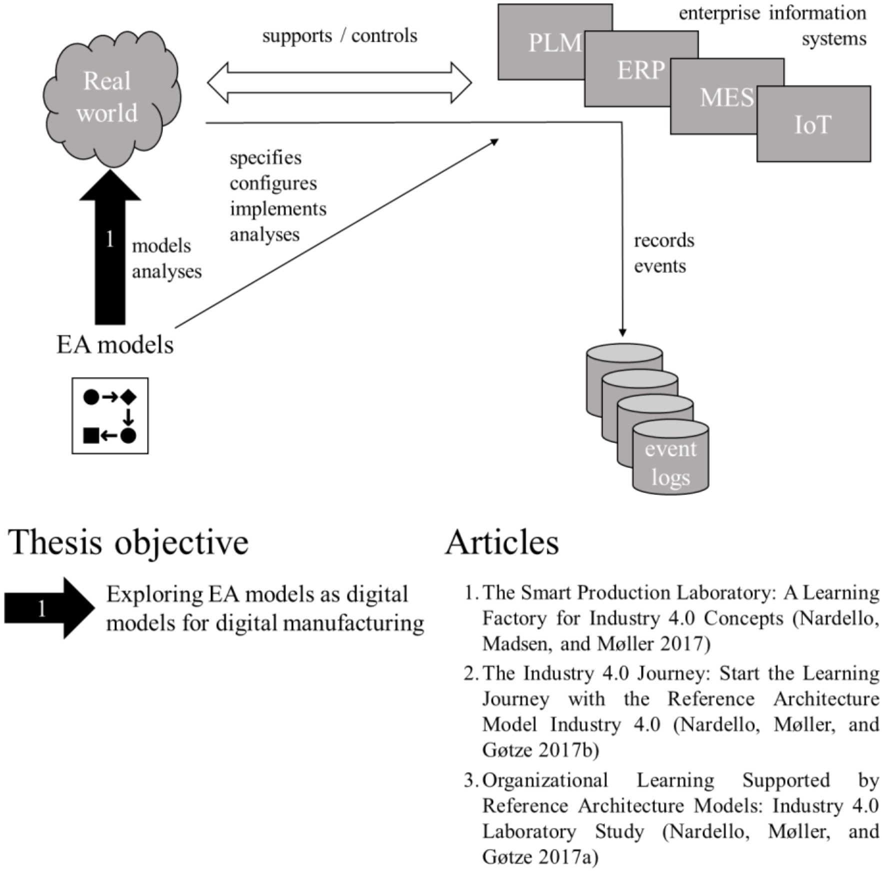


Figure 11. Theoretical framework for the first thesis objective

4.1. ARTICLE 1, LEARNING FACTORY

This article investigated the following research questions:

> What components are required in a learning factory in order to conduct research on digital manufacturing?
>
> How are research and education on digital manufacturing conducted in a learning factory?

To share the empirical context of this thesis with the relevant research community, this article investigated those components in the learning factory that enable research on digital manufacturing and explained how research on digital manufacturing is undertaken in a learning factory environment. The contributions of this article

(Nardello, Madsen, and Møller 2017) are complemented when necessary by those of the other articles.

A learning factory is a facility established to support research projects. It replicates industrial environments as closely as possible, and it is equipped with machines and systems used in industry (Abele et al. 2015). The learning factory at Aalborg University is focused on digital manufacturing. It is intended to support the development of new technologies for the manufacturing industry. It provides an empirical context for research and the development of solutions and their integration in a manufacturing environment. In addition, Aalborg University's learning factory is intended to be a demonstrator that presents the potential of new technologies and solutions to both research and practitioner communities. Figure 12 provides an overview of the learning factory at Aalborg University.

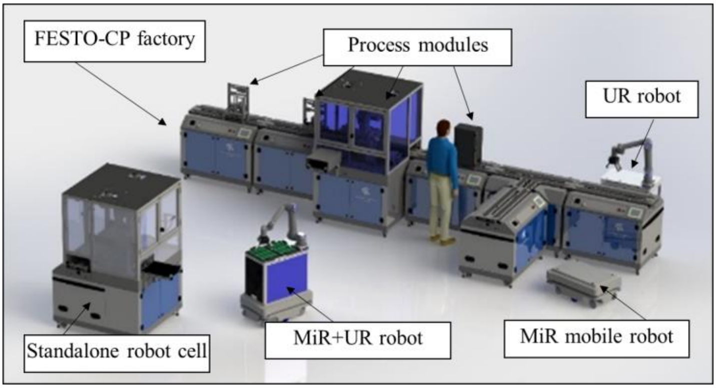


Figure 12. Learning factory at Aalborg University (Nardello, Madsen, and Møller 2017)

The learning factory includes transporting and processing modules, as well as different kinds of robots (Nardello, Madsen, and Møller 2017). The FESTOs CP factory (Festo Didactic 2017) is a modular and expandable factory composed of six transportation modules (linear conveyor belts) and one branch module. Each of these modules has mechanical, electrical, and software interfaces. The process modules are mounted on the transportation modules. The modules installed in the initial configuration of the learning factory were a part dispenser, a drilling module, an assembly module, and an inspection module. The robots are a dedicated robot (KUKA) in the assembly cell, mobile robots (MiR), and collaborative robots (UR-robots). The MiR and UR robots are used to automate the packaging of products. The standalone robot cell is used for various tasks, such as the disassembly of the product.

The products and materials used at the learning factory change based on the projects currently undertaken. When the learning factory was first established, it assembled a simplified mobile phone (Nardello, Møller, and Gøtze 2017a). As shown in Figure 13, the phone had four components: a back cover, a top cover, a circuit board, and one or two fuses. There are several product variants, for example a phone with no fuse, only a left fuse, only a right fuse, and both fuses.

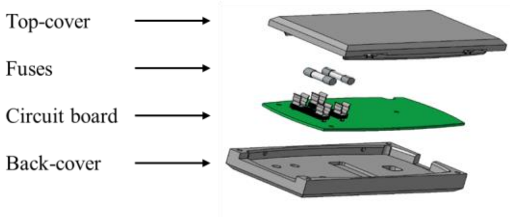


Figure 13. Learning factory product, a simplified mobile phone (Nardello, Møller, and Gøtze 2017a)

The production process is the following:

1. The back cover is placed on a carrier by the part dispenser module;
2. Four holes are drilled into the back cover by the drilling module;
3. Circuit board and fuses are assembled by the KUKA robot at the assembly module;
4. The quality of the product is checked by the inspection module;
5. The top cover is applied by a human operator;
6. The product is removed from the carrier and placed in an area reserved for finished products by the MiR and UR robots.

There are two main enterprise information systems at the learning factory, MES and SAP ERP. Both systems store information about the production process. The FESTO MES monitors the status of the process and transportation modules and controls the production process. These enterprise information systems are very similar to, if not exactly the same as, systems used in industry. When the learning factory was first established, there were few digital models of the process, and transportation modules were used for simulation purposes.

There are several groups of people involved in and who interact with this learning factory (Nardello, Madsen, and Møller 2017). The manager of the learning factory maintains the facility. The research community is composed of researchers, PhD candidates, postdoctoral researchers, and professors. Bachelor’s and master’s students use the learning factory for their semester projects. Practitioners from manufacturing companies, technology vendors, and system integrators are also involved in the learning factory.

4.2. ARTICLE 2

The learning factory manager raised two problems also experienced in industry, namely the difficulty of accessing data and information about the learning factory and the lack of a common understanding of the resources available at and the processes of the learning factory. To address these problems, RAMI4.0 and organizational learning research was included in the article. As presented in Section 2.1.2, RAMI4.0 provides a structure with which to model digital manufacturing. Organizational learning is "the process by which new knowledge or insights are developed by a firm" (Tippins and Sohi 2003). In this case, the firm is the learning factory and the people involved in it. The organizational learning process is divided into four sub-processes (Slater and Narver 1995): information acquisition, information dissemination, shared interpretation, and the development of organizational memory.

To address the problems mentioned above, article 2 investigated the following research questions:

> How does an instantiation of RAMI4.0 with EA models contribute to organizational learning?
>
> How does an instantiation of RAMI4.0 with EA models contribute to the information dissemination sub-process?

4.2.1. EA MODELS

To address these research questions, each architecture layer of RAMI4.0 was instantiated with EA models available in QualiWare's EA repository (Nardello, Møller, and Gøtze 2017b). The business layer (Figure 14a) was represented in a strategic model that included business goals, capabilities, and enterprise processes. The functional layer (Figure 14b) was documented with a focus on the assembly process. It was a process model that included activities, equipment, and product parts. The information layer (Figure 14c) was represented with a data model that included properties and attributes for each physical asset (e.g. back cover, drilling equipment). The communication layer (Figure 14d) was documented with an application model that modelled the interaction between MES on the one hand and the process and transportation modules on the other. The integration layer (Figure 14e) was represented with an infrastructure and communication model that focused on the physical interaction between the carrier and transportation module. The asset layer (Figure 14f) was documented with a product model. The model specified the phone and its components. RAMI4.0 structured information about the learning factory, and the EA models used made this information available to the individuals involved in the learning factory.

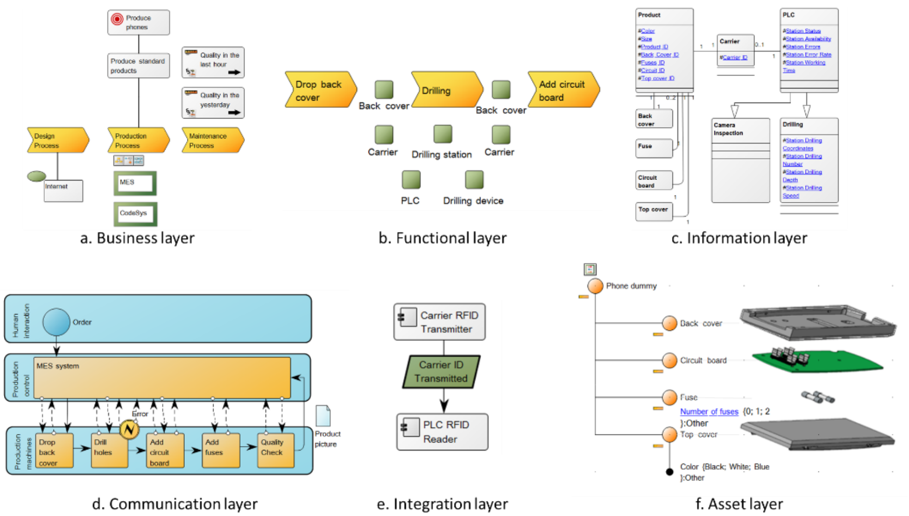


Figure 14. Instantiation of RAMI4.0 architecture layers with EA models (Nardello, Møller, and Gøtze 2017b).

4.2.2. CONTRIBUTIONS TO ORGANIZATIONAL LEARNING AND INFORMATION DISSEMINATION SUB-PROCESS

The contributions of the EA models to organizational learning and the information dissemination sub-process were assessed in an interview with the learning factory manager. The main contributions were as follows:

- EA models instantiating RAMI4.0 helped the manager to monitor how the process modules are connected and to obtain information about the learning factory.
- EA models supported the explanation of the production process to new people.
- EA models supported the collection of information by structuring it.
- EA models represented the learning factory and provided the manager with up-to-date and relevant information about it.

4.3. ARTICLE 3

This article (Nardello, Møller, and Gøtze 2017a) is an extension of the previous one (Nardello, Møller, and Gøtze 2017b). The background and research and practice problems are the same for both articles. Therefore, this section focuses on the new contributions of article 3. This article also investigated the following research question:

Which EA models instantiate RAMI4.0?

4.3.1. EA MODELS

In addition to the EA model presented previously, this article included an EA model, with the intention being to provide an overview of all of the other EA models. This overview is provided in Figure 15. A definition of each RAMI4.0 layer is provided in the column on the right-hand side of the figure.

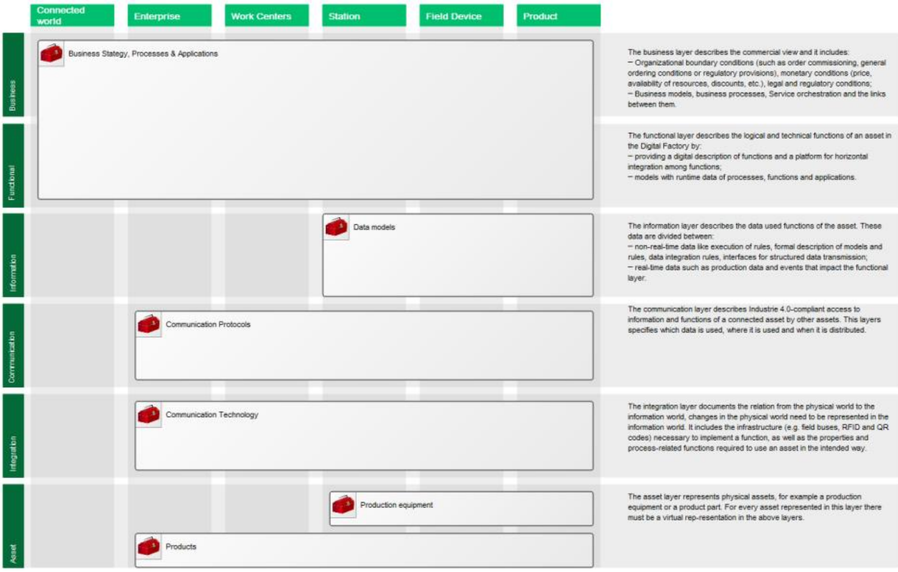


Figure 15. Overview of the EA models used to instantiate RAMI4.0 (Nardello, Møller, and Gøtze 2017a).

As shown in Figure 16, this article also presents the full version of the process model used to instantiate the functional layer of RAMI4.0.

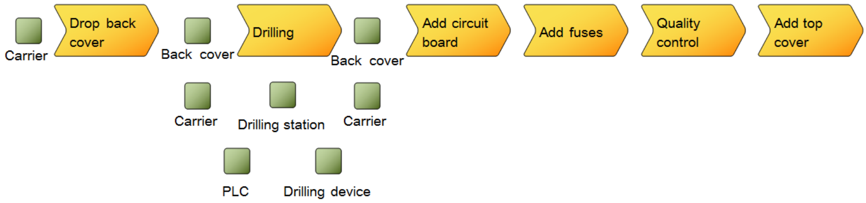


Figure 16. Instantiation of the functional layer of RAMI4.0 with a process model (Nardello, Møller, and Gøtze 2017a).

In addition to the product model, the instantiation of the asset layer of RAMI4.0 was performed with the instantiation of an equipment model. As shown in Figure 17, this model represented the learning factory's drilling equipment and its sensors.

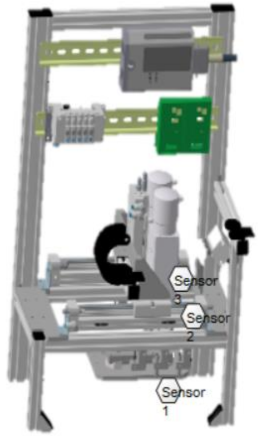


Figure 17. Instantiation of the asset layer of RAMI4.0 with an equipment model (Nardello, Møller, and Gøtze 2017a).

Therefore, RAMI4.0 was instantiated with the following EA models: strategic, process, data, application, infrastructure and communication, product, and equipment model.

4.3.2. MODELLING APPROACH

To instantiate RAMI4.0 through EA models, the author adopted both top-down and bottom-up approaches (Arsanjani 2004). The approaches employed stem from service-oriented architecture modelling. The modelling started with EA models for instantiating the business and asset layers. Thereafter, it focused on the functional and integration layers. Finally, it modelled the information and communication layers. When the EA models were created, the relationships between the elements in the EA models were established. Using this approach, it was possible to navigate from elements in the business layer down to elements in the asset layer and vice versa.

4.4. ADDITIONAL INSIGHTS AND REFLECTIONS

This section begins by continuing the evaluation of the EA models. It then turns to a comparison between Aalborg University's learning factory and other learning factories for digital manufacturing. Furthermore, it provides additional insights concerning the EA models gathered from practice following the publication of the articles.

The efficacy, utility, and usability of the EA models were evaluated with the learning factory manager. For efficacy, the EA models developed by the author were able to instantiate all RAMI4.0 layers. For utility, the manager thought that the EA models were very useful in addressing the information dissemination problem. For usability, the manager stated that he was able to use the EA models developed.

The author and his colleagues also had opportunities to visit other universities' learning factories. In September 2018, they visited the learning factories for digital manufacturing at Technische Universität Darmstadt in Germany, a leading European engineering university. The purpose and groups of users of this learning factory were aligned with those at Aalborg University. This learning factory has also been used to conduct research on digital manufacturing. In May 2019, the author and his colleagues visited the University of Bergamo and shared with the local researchers their research initiatives. This university had industrial equipment with which to conduct research, but this equipment was not part of a learning factory. Also in this case, the equipment was used to conduct research on digital manufacturing. These universities and their research contexts on digital manufacturing are similar to the learning factory at Aalborg University.

Once the articles had been published, the EA models instantiating RAMI4.0 were presented at several academic and practitioners' events. The discussions at these events led to three additional insights.
First, EA models are mostly applied to represent concepts rather than physical entities. Although it is important for EA discipline to be used to create digital models of manufacturing, existing EA models are subject to important limitations. It is important to model products, equipment, and their components, and existing EA models support the modelling of their physical characteristics and design only to a limited degree (e.g. 3D models).
Second, standards for digital manufacturing such as RAMI4.0 are through a dedicated fast-track process in standardization organizations (ISO and IEC). Therefore, it is expected that more standards will be developed soon. New approaches to EA that enable the implementation of these standards and can improve information sharing with little modelling are required. Furthermore, EA can support the identification of

the data required to create digital models of products, manufacturing, and an enterprise based on EA models.

Third, the more detailed and physical the object being modelled, the closer the EA model is to the data. Most of the information concerning the development of the EA models for instantiating RAMI4.0 was obtained from the enterprise information systems at the learning factory. Therefore, there should be a solution that leverages data to create, or support the creation of, EA models. This solution would make it possible to represent smart products, as they include data, and support functional units in understand smart products and their data, which is currently difficult to access.

Third, the discussions also led to the identification of the following limitations of the EA models used to instantiate RAMI4.0:

- The business layer includes monetary and legal conditions that are not included in the EA models instantiated.
- The functional layer includes a description of the functions of an asset. The EA models instantiated focused on the description of the production process. Other descriptions of how the asset functions are not included. Process models and other EA models can be used to model the functions of an asset. Furthermore, the process model developed lacks relationship elements (i.e. arrows) in the process model.
- The asset layer represented through the equipment model is very limited, as it takes the form of an image with sensor elements on top. This model should more closely resemble a computer-aided design drawing of the equipment.

4.5. RESEARCH CONTRIBUTIONS

This section summarizes the research contribution presented above, with the summary being presented in two parts. The first part focuses on the identification of the EA models used to instantiate RAMI4.0 and the approach used. The second part addresses the use of the EA models to support structuring data and information and to facilitate information dissemination.

4.5.1. EA MODELS TO INSTANTIATE RAMI4.0

The EA models used to instantiate RAMI4.0 were the following:

- Business layer, strategic model
- Functional layer, process model
- Information layer, data model
- Communication layer, application model
- Integration layer, infrastructure and communication model
- Product asset layer, product model
- Equipment asset layer, equipment model

Although the instantiation covered all RAMI4.0 architecture layers, future research could be conducted to complete the modelling of the following layers:

- The business layer could be addressed by developing EA models that include monetary and legal conditions.
- The functional layer could be addressed by developing EA models that include other functions.
- The product and equipment asset layer could be addressed by developing EA models that improve the modelling of physical characteristics and the design of products in EA models (e.g. 3D models).

Both a top-down and a bottom-up approach were used to instantiate RAMI4.0. This approach was used to model both high- and low-level aspects. The EA models created enabled navigation from elements in the business layer to elements in the asset layer and vice versa.

4.5.2. EA MODELS FOR DIGITAL MANUFACTURING FACILITATE INFORMATION DISSEMINATION

Enterprise architecture models for digital manufacturing address the two problems of the difficulty of accessing data and information and the lack of a common understanding of the resources and processes associated with digital manufacturing. The research contributions for this objective are the following:

1. Enterprise architecture models can instantiate RAMI4.0 and can be used as digital models for digital manufacturing.

2. Enterprise architecture models for digital manufacturing facilitate information dissemination.

Related to the first problem, EA models for digital manufacturing supported the structuring of information. They helped the manager to understand how the products, equipment, process, and components were related. In addition, the EA models provided up-to-date and relevant information about the learning factory. Furthermore, the EA models provided a framework that supports the collection of new information.

With regard to the second problem, EA models for digital manufacturing contributed to facilitating information dissemination in a digital manufacturing context. The EA models supported explaining the production process to new staff and promoting a common understanding of resources and process.

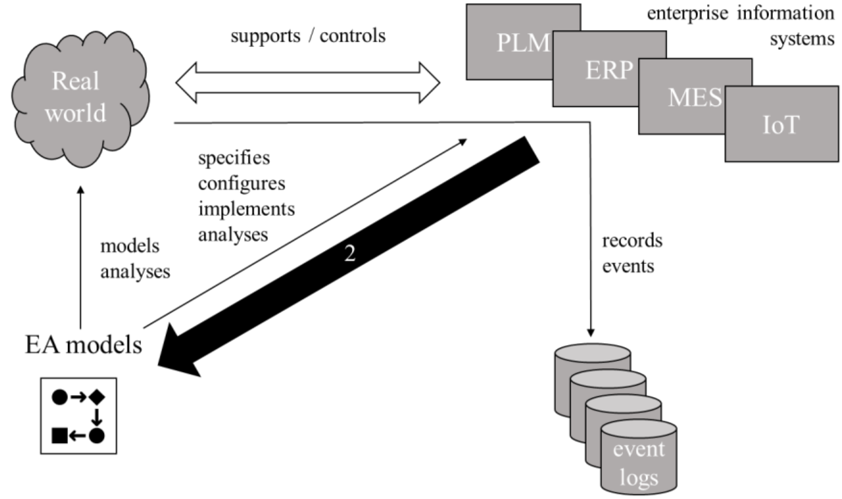
CHAPTER 5. USING DATA TO CREATE EA MODELS FOR DIGITAL MANUFACTURING

This chapter presents the research findings related to the second thesis objective. Articles 4, 5, and 6 are summarized by reviewing their respective research questions and contents. Article 4 initiated the research intended to develop a new automated EA modelling method. Articles 5 and 6 presented the AMA4EA method and the extended AMA4EA method. Thereafter, additional insights from and reflections on the articles are presented. Finally, the contributions of the articles are summarized to address the research questions at the level of this thesis' objectives. The summary presented in the final section is then synthesized in Chapter 7.

This chapter presents the articles relevant to the following research question:

> How are EA models for digital manufacturing created from the data stored enterprise information systems?

To explore the concept of creating EA models from data, the following articles were written. Article 4 represented the beginning of the author's research into the above research question by exploring the role of abstraction in EA modelling and automated EA modelling methods. Article 5 identified the components that an automated EA modelling method requires to model business aspects and presented the AMA4EA method, while Article 6 extended the AMA4EA method to address the problem of process heterogeneity.



Thesis objective

2 Using data to create EA models for digital manufacturing

Articles

4. Process Model Automation For Industry 4.0: Challenges For Automated Model Generation Based On Laboratory Experiments (Nardello, Møller, and Gøtze 2018)
5. Automated Modeling with Abstraction for Enterprise Architecture (AMA4EA): Business Process Model Automation in an Industry 4.0 (Nardello et al. 2019a)
6. Incorporating Process and Data Heterogeneity in Enterprise Architecture: Extended AMA4EA in an International Manufacturing Company (Nardello et al. 2019b)

Figure 18. Theoretical framework for the second thesis objective.

5.1. ARTICLE 4

RAMI 4.0 and the EA models that instantiate it covered the business, application, and technology aspects. However, as reported in Section 2.4, existing automated EA modelling methods focus on the application and technology aspects. Therefore, there is a lack of an efficient modelling approach capable of addressing all EA aspects, particularly the business aspect. The problem of creating EA models of the business aspect based on data is related to abstraction. In fact, while data about server configurations and data models can be reported as it is stored on an enterprise information system in the EA models, data for the EA models related to the business aspects needs to be abstracted to be understandable.

Therefore, this article focused on the problems associated with automated EA methods related to abstraction. The research questions were the following:

> How to include abstraction in a new automated EA modelling method?
>
> What are the challenges associated with introducing abstraction in a new automated EA modelling method?

To address lack of an efficient modelling approach capable of addressing all EA aspects, particularly the business aspect, EA modelling process and the creation of EA models from (Lankhorst et al. 2017) were analysed. As shown in the top part of Figure 19, the EA modelling process consists of five activities: (1) establishing the purpose, scope, and focus; (2) selection of the viewpoints; (3) creating and structuring the model; (4) visualizing the model; and (5) maintenance of the model. Focusing on the creating and structuring of the model activity, as shown in the middle part of Figure 19, Lankhorst et al. (2017) divide this activity into three actions: (1) analysing existing information, (2) gathering new information, and (3) structuring the EA model.

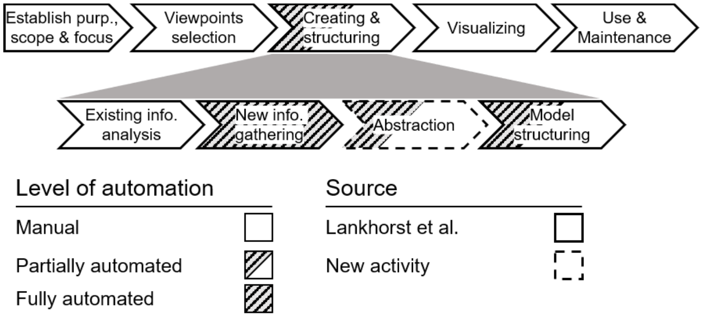


Figure 19. Enterprise architecture modelling process of Lankhorst et al. (2017) *with the addition of the abstraction action (Nardello, Møller, and Gøtze 2018)*

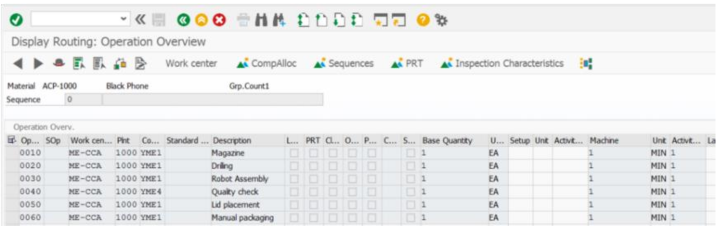
5.1.1. NEW AUTOMATED EA MODELLING METHOD

The article presents a new method for automated EA modelling. This method is a revised version of the creating and structuring activity found in EA modelling with an explicit abstraction action and a classification of the level of automation of the actions involved in the creating and structuring activity. Each action in the revised version of the creating a structure activity has two types of task, both of which are necessary for automated modelling: meta-model and instance tasks. The meta-model tasks define "the frames, rules, and constraints of the automatically generated models" (Nardello, Møller, and Gøtze 2018, 207), while the instance tasks are required for the development of a specific instance of the model (Nardello, Møller, and Gøtze 2018, 207). Descriptions of each action are available in Nardello, Møller, and Gøtze (2018, 208).

5.1.2. EMPIRICAL CASE

The new automated EA modelling method was applied in the learning factory. Figure 20 documents the execution of each action in the method in the form of screenshots. The data concerning a production process was extracted from SAP ERP and FESTO MES (Figure 20a). To support the abstraction of data, the production process classification was applied (Sorensen, Brunoe, and Nielsen 2018), as it was used in the MADE manufacturing companies. The classification organizes production processes into four levels of detail: four process categories, 16 process families, 53 process classes, and 232 process subclasses. A Microsoft Excel file was used to abstract the data with the production process classification (Figure 20b and c). Finally, the author, with the support of software developers from QualiWare ApS, developed an algorithm with which to import the file into the EA repository and create a process model based on it (Figure 20d).

a. Existing information analysis


Display Routing: Operation Overview

Work center | CompAlloc | Sequences | PRT | Inspection Characteristics

Material ACP-1000 Black Phone Grp.Count1

Sequence 0

Operation Overv.

Op...	SOp	Work cen...	Plnt	Co...	Standard ...	Description	L...	PRT	Cl...	O...	P...	C...	S...	Base Quantity	U...	Setup	Unit	Activt...	Machine	Unit	Activt...	La
0010		ME-CCA	1000	YME1		Magazine								1	EA				1	MIN	1	
0020		ME-CCA	1000	YME1		Drilling								1	EA				1	MIN	1	
0030		ME-CCA	1000	YME1		Robot Assembly								1	EA				1	MIN	1	
0040		ME-CCA	1000	YME4		Quality check								1	EA				1	MIN	1	
0050		ME-CCA	1000	YME1		Lid placement								1	EA				1	MIN	1	
0060		ME-CCA	1000	YME1		Manual packaging								1	EA				1	MIN	1	

b. New information gathering

Operation	SOp	Work center	Plnt	Control Key	Description	Base Quantity	Unit of measure	Machine	Unit	Activity Type
10		ME-CCA	1000	YME1	Magazine	1	EA	1	MIN	1
20		ME-CCA	1000	YME1	Drilling	1	EA	1	MIN	1
30		ME-CCA	1000	YME1	Robot Assembly	1	EA	1	MIN	1
40		ME-CCA	1000	YME4	Quality check	1	EA	1	MIN	1
50		ME-CCA	1000	YME1	Lid placement	1	EA	1	MIN	1
60		ME-CCA	1000	YME1	Manual packaging	1	EA	1	MIN	1

c. Abstraction

Process category	Process families	Process classes	Process subclasses	Name in QualiWare (the most detailed value available in the classification)
MaterialHandling	Handling	ChangeQuantities	Allocate	Allocate from Magazine
Manufacturing	Separating	Cutting_Chips	Drilling	Drilling
Manufacturing	Joining	Assembly	Lay&PutOn	Lay&PutOn Components
Test&Inspection	Inspection	CheckProperties		CheckProperties Components placement
Manufacturing	Joining	Assembly	Lay&PutOn	Lay&PutOn Lid
MaterialHandling	UnitLoadFormation	Packaging		Packaging manual

d. Model structuring

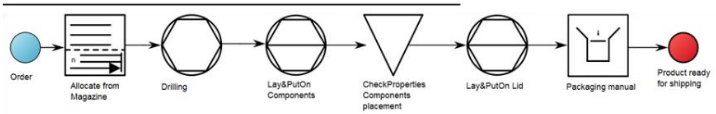


Figure 20. Application of the new automated EA modelling method at the learning factory at Aalborg University (Nardello, Møller, and Gøtze 2018)

5.1.3. EMPIRICAL EVALUATION

The application and outcome of the method were evaluated by the learning factory manager. The main outcome was that the data on the production process was easily shared. The manager stated that the use of the production process classification to abstract the data in the ERP and MES and the visualization of the process in an EA model made the process understandable to people who had not worked with these specific systems previously.

5.1.4. NEW CHALLENGES

Based on the application of the method in an empirical context, article 4 identified challenges associated with automated EA modelling that may represent future research (Nardello, Møller, and Gøtze 2018, 212):

1. How can interaction with the domain expert be improved? In which of the automated EA modelling method's tasks should a domain expert be involved?
2. How can multiple people be involved in the abstraction action? Which collaboration technique(s) can be applied?
3. How different data sources for automated EA modelling can be included?
4. How can changes in reality be managed and displayed in EA models?

5.2. ARTICLE 5

This article (Nardello et al. 2019a) is an extension of the previous one (Nardello, Møller, and Gøtze 2018). The background and research and practice problems are the same for both articles. It further continued the work of the previous article by investigating the following research question:

> What components are necessary in an automated EA modelling method that abstracts data to EA models related to the business aspect?

To address this research question, existing research on abstraction in EA modelling was analysed. This led to the identification of abstraction types that were used to analyse existing automated EA modelling methods. The outcome of this analysis is presented in Table 3 and is described in more detail in the article.

Table 3. Abstraction types in automated EA modelling methods (Nardello et al. 2019a)

Abstraction types	Farwick et al. (2016)	Buschle et al. (2011)	Holm et al. (2014)	Välja et al. (2015)	Välja et al. (2016)
Abstraction levels					
Business level	N/A	N/A	(X)[13]	N/A	N/A
Application level	X	X	X	N/A	X
Technology level	X	X	X	X	X
Abstraction from aspects	N/A	N/A	X	N/A	N/A
Abstraction from properties	X	X	X	X	X
Generalization	X	N/A	X	N/A	X
Hierarchical					
Structural abstraction	N/A	N/A	N/A	N/A	N/A
Functional abstraction	N/A	N/A	N/A	N/A	N/A

Based on this analysis, three problems associated with automated EA modelling methods were identified: first, the insufficient coverage of the business abstraction level. The second issue is the fact that data from enterprise information systems is too detailed to be useful for creating EA models. The third problem is the superficial explanations of existing methods, which inhibit their implementation.

5.2.1. AMA4EA

To address the abovementioned problems, the method proposed in the previous article was significantly revised. The method with meta-model and instance tasks based on the EA modelling process (Lankhorst et al. 2017) was transformed into a new automated EA modelling method, Automated Modelling with Abstraction for EA (AMA4EA).

AMA4EA is a method by which to "automatically abstract detailed data from ESs [enterprise systems] to concepts. The abstraction is achieved through the use of [the] AMA4EA environment. [The] AMA4EA environment is a system that abstracts data, for example from ESs, following predefined abstraction hierarchies. AMA4EA also instantiates the relevant information in an EA repository and creates EA models

[13] Limited coverage

automatically" (Nardello et al. 2019a). The AMA4EA method requires four roles: a stakeholder (S), who initiates the modelling and setting the requirements; an enterprise architect (A), who manages the execution of AMA4EA; a data source manager (DSM), who provides data for AMA4EA; and a subject-matter expert (SME), who collaborates with the architect in defining the abstraction hierarchies and performing abstractions. The AMA4EA method is divided into preparation and execution phases (Nardello et al. 2019a), which are summarized in Figure 21 and Figure 22, and Table 4 and Table 5, respectively.

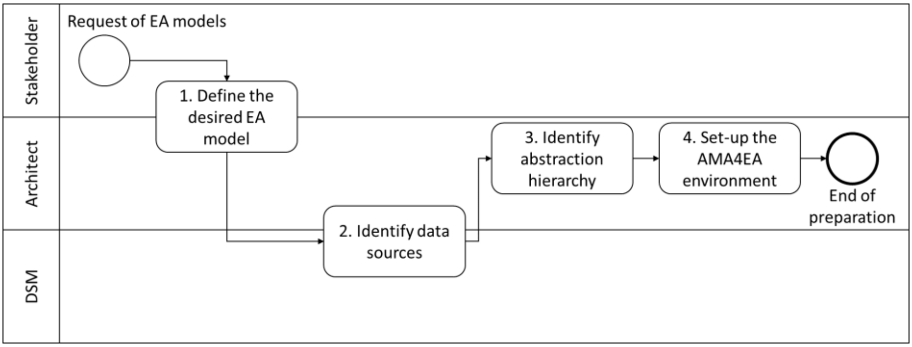


Figure 21. The four activities in the preparation phase of the AMA4EA method (Nardello et al. 2019b)

Table 4. The four activities in the preparation phase of the AMA4EA method (Nardello et al. 2019b)

Activity	**Description of AMA4EA**
1. Define the desired EA model	The architect and the stakeholder define the desired EA model's purpose, scope, and concepts. They decide the desired EA model's abstraction level—business, application, or technology. The architect then chooses the desired type of EA model (e.g. business process model, product architecture model, or strategy model) and the modelling notation (e.g. ArchiMate, BPMN, UML, or an industry- or enterprise-specific notation).
2. Identify data sources	The architect and DSM specify which ES will handle the data related to the desired EA model's concepts. They locate the relevant data in the ES and identify the data’s structural metadata. From the structural metadata, the architect and DSM choose the fields required for the desired EA model. In addition, they indicate the interfaces available for extracting data from the ES.
3. Identify abstraction hierarchy	The architect selects an abstraction hierarchy aligned with the desired EA model's purpose, scope, and concepts. Should no suitable abstraction hierarchies exist, the SME and architect may search for one (e.g. industrial standards). If no satisfactory abstraction hierarchies are found, they can develop a new one. In the last two cases, the architect will import the abstraction hierarchy into the AMA4EA environment and into an EA repository.
4. Set up the AMA4EA environment	This activity is divided into two tasks: In the first task, the architect creates a storage area in the AMA4EA environment that replicates the ES's structural metadata. Using this approach, data from ESs can be automatically imported into the AMA4EA environment. In the second task, the architect defines the structural metadata of the AMA4EA environment's interface. The first section of the interface relates to fields from the dedicated data storage area, while the second contains information required for performing abstractions. The second section includes the concepts and relationships in the abstraction hierarchy. The third section includes the information required for mapping fields from the ES structural metadata to the meta-model of the elements in the EA repository.

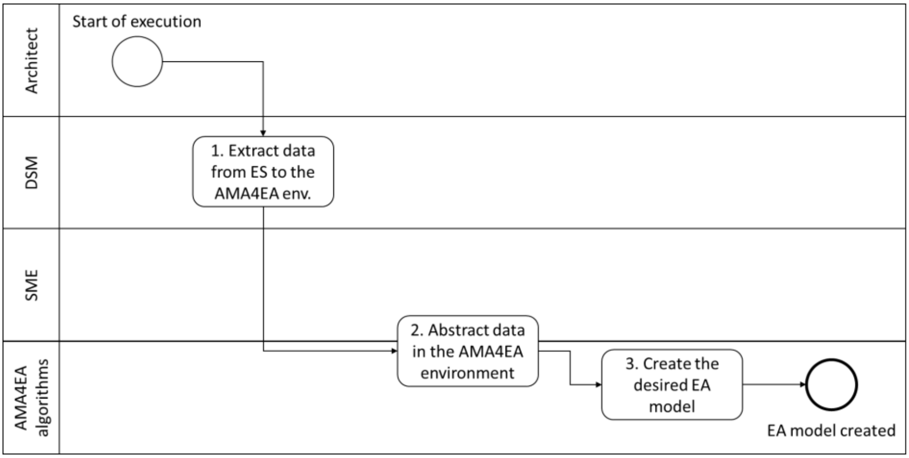


Figure 22. The three activities in the execution phase of the AMA4EA method (Nardello et al. 2019b)

Table 5. The three activities in the execution phase of the AMA4EA method (Nardello et al. 2019b)

Activity	**Description of AMA4EA**
1. Extract data from the ES to the AMA4EA environment	The DSM exports data from an ES. The data is then automatically imported into AMA4EA using the *data import algorithm*. The algorithm stores the data in the dedicated storage area in the AMA4EA environment.
2. Abstract data in the AMA4EA environment	The *abstraction algorithm* retrieves previous abstractions from the AMA4EA environment and applies them to the data under analysis. If the data cannot be automatically abstracted, the SME is requested to manually abstract them. The *abstraction algorithm* reduces manual abstractions in the AMA4EA environment.
3. Create the desired EA model	The *instantiate and position algorithm* is responsible for importing data and abstractions thereof from the AMA4EA environment into the EA repository. This algorithm instantiates new elements in the EA repository and stores the abstractions in the elements' fields. The algorithm also creates the desired EA model and positions the instantiated elements in that model.

5.2.2. EMPIRICAL CASE

The AMA4EA method was applied in the learning factory at Aalborg University. Figure 23 documents the execution of the method in the form of screenshots. The AMA4EA method abstracted detailed data from the ERP system and MES to create an EA model at the business level. The method provided a simplified visualization of production process data through an automatically created business process model. As shown in Figure 24, two versions of the EA model were developed. The first version visually depicted the data in the EA model without abstraction, while the second one with abstraction.

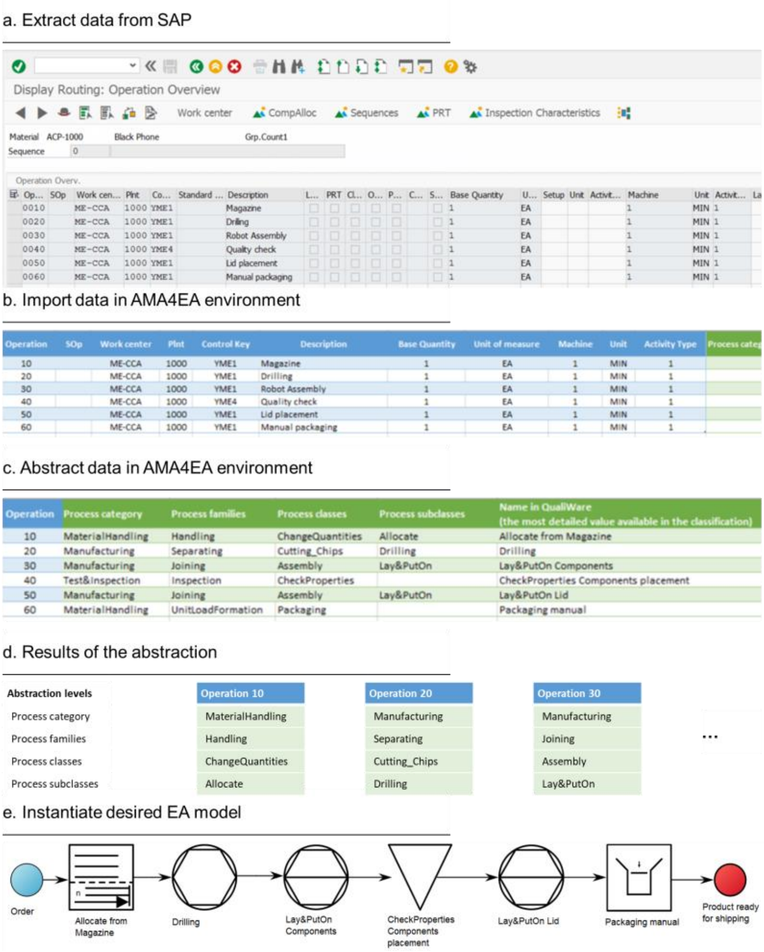


Figure 23. Application of the AMA4EA method at the learning factory at Aalborg University (Nardello et al. 2019a)

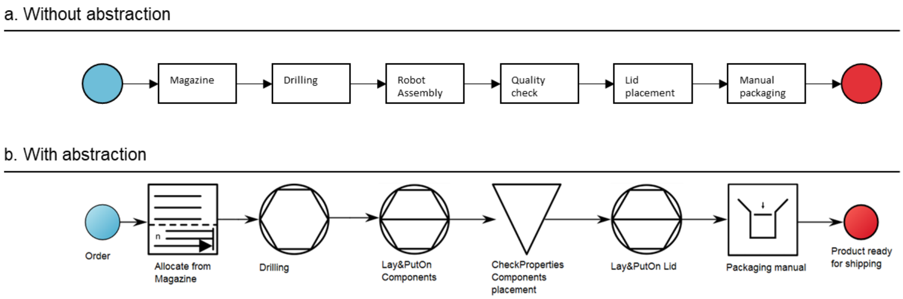


Figure 24. Comparison between execution of the EA model with and without abstraction (Nardello et al. 2019a)

5.2.3. EVALUATION

The outcome of the application of the AMA4EA method and its artefacts were identical to those presented in article 4. Therefore, the evaluation of this method is based on the interview with the learning factory manager mentioned in article 4. The main outcomes were the following:

1. The AMA4EA method was usable, and the manager could have executed it himself.
2. The AMA4EA method was useful, as it abstracted data from SAP ERP and FESTO MES4 in a manner that was understandable by stakeholders without previous experience with the systems.
3. The EA model without abstraction (Figure 24a) was difficult to understand because the data related to the production process was unclear and included very little information.
4. The EA model with abstraction (Figure 24b) was a major improvement on the other model. Practitioners could understand more of the information provided by the EA model that featured abstraction.

5.3. ARTICLE 6

In this article the AMA4EA method was applied with production process data from an international manufacturing company. As a result, a new problem emerged: The production sites of these companies are located in heterogeneous environments (Ghoshal and Nahria 1989) due to different historical and environmental conditions (Ghoshal and Nahria 1989). Production processes and enterprise information systems vary across sites. Therefore, the production process data in the ERP system is heterogeneous because the processes conducted at these sites are heterogeneous. A component's production process was specified varies depending on the site. At one production site, a particular process was divided into 26 activities, while, at another, it consisted of over 200 activities.

To address this problem, this article investigated the following research question:

> How to further develop automated EA modelling methods that model business aspects to address with process heterogeneity?

5.3.1. EXTENDED AMA4EA FOR PROCESS HETEROGENEITY

To address the problem of process heterogeneity, the AMA4EA method was extended to create EA models at both the site and enterprise levels: "Heterogeneous production processes at a site level are related to the overview of the production processes at an enterprise level" (Nardello et al. 2019b). An EA model at the enterprise level is used to provide an overview of production processes, along with their sub-processes, as shown in Figure 25. An EA model at the site level can be used to specify the sub-processes in the activities performed at the sites, as shown in Figure 25**.** As a result, EA models at the site and enterprise levels are connected through sub-processes. The extensions of the activities in the preparation and execution phases of the AMA4EA method are presented in Table 6 and Table 7, respectively.

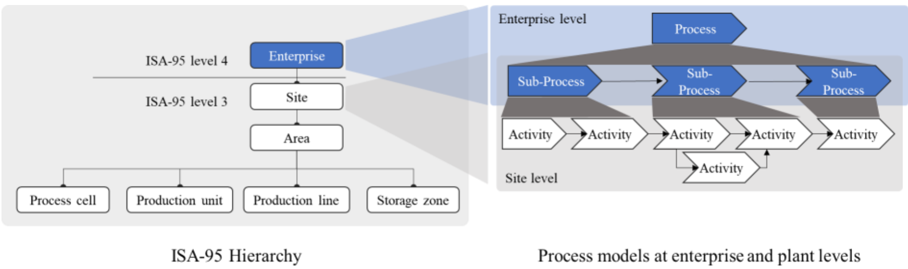


Figure 25. Hierarchical levels of ISA-95 adapted from (International Electrotechnical Commission 2017; Nardello, Møller, and Gøtze 2017a) and the relationship between process models at the enterprise and site levels (Nardello et al. 2019b).

Table 6. Extension of the four activities in the preparation phase of the AMA4EA method for incorporating process heterogeneity (Nardello et al. 2019b)

Activity	**Description of AMA4EA**
1. Define the desired EA model	The stakeholder and the architect acknowledge the need to manage EA models at two levels of detail. This requires defining the purpose, scope, and concepts at each level. In addition to choosing the type of EA model, the stakeholder and the architect decide upon the modelling notation for each level, which can differ. *Input:* The stakeholder presents his or her understanding of the problem addressed with the EA models. *Output:* Definition of the desired EA models, the scope of the models, and the notation to be used.
2. Identify data sources	The DSM identifies the ESs that store data related to the concepts to be included in the desired EA model and the location of the relevant data in the ESs. For example, production routing data in an ERP system is related to production processes. *Input:* Purpose, scope, and concepts to be included in the EA models. *Output:* Names of the ESs with the relevant data and the location where the data should be extracted.
3. Identify abstraction hierarchy	The architect selects the abstraction hierarchies relevant to abstracting the data from the ESs to the concepts in the EA model at the enterprise and site levels. If no suitable abstraction hierarchies exist, the SME and architect may search for one (e.g. industry standards). If no satisfactory abstraction hierarchies are found, they can develop a new one. If this is the first application of the abstraction hierarchies, the architect will import them into the AMA4EA environment and into an EA repository. *Input:* Modelling notation selected in the first activity. *Output:* Abstraction hierarchy with the concepts that will be represented in the EA models.
4. Set up the AMA4EA environment	For the EA model at the enterprise level, this activity does not change. For the EA model at the site level, this activity needs to duplicate the "main" interface to create a "site" interface. The architect needs to extend the structural metadata of the AMA4EA environment's "site" interface by adding columns for the fields and abstractions of the data for the EA model at the enterprise level. As a result, through the "site" interface, it will be possible to specify the mapping from the data for the EA models at the site level to the EA model at the enterprise level. *Input:* AMA4EA environment with only the "main" interface. *Output:* AMA4EA environment with "main" and "site" interfaces, as well as a site interface that allows mapping the data and abstraction from the site level to the enterprise level.

Table 7. Extension of the three activities in the execution phase of AMA4EA for incorporating process heterogeneity (Nardello et al. 2019b)

Activity	**Description of AMA4EA**
1. Extract data from ES to the AMA4EA environment	Enterprise integration software or the DSM extracts data from the ESs for creating the EA models previously identified. The data is imported into the dedicated storage area in the AMA4EA environment using the *data import algorithm*. *Input:* Names of the ESs with the data for the EA models and the locations where the data should be extracted. *Output:* AMA4EA environment with data from the ESs in the “main” and “site” interfaces.
2. Abstract data in the AMA4EA environment	This extension is executed after the abstraction from data to concepts using the abstraction hierarchy. In the “site” interface, the *abstraction algorithm* or the SME maps concepts at the site level to the concepts at the enterprise level. For instance, each activity in the production process at the site level is mapped to a sub-process of the process at the enterprise level. *Input:* AMA4EA environment with data from the ESs in the “main” and “site” interfaces. *Output:* AMA4EA environment in which the data has been abstracted to concepts for both the enterprise and site levels. In addition, the “site” interface maps the concepts at the site level to the concepts at the enterprise level.
3. Create the desired EA model	The *instantiate and position algorithm* imports all of the data, abstractions, and mappings in the “main” and “site” interfaces of the AMA4EA environment to the EA repository. The algorithm instantiates an EA model at the enterprise level using the data and abstractions from the “main” interface. The algorithm also instantiates an EA model for each concept at the enterprise level with the concepts at a site level mapped in the "site" interface. For instance, the algorithm instantiates one EA model for the process at the enterprise level with the sub-processes, as well as EA models that specify the activities involved in each of the sub-processes at the site level. *Input:* The output of the previous activity. *Output:* An EA model with the concepts at the enterprise level and EA models that map these concepts at the site level.

5.3.2. EMPIRICAL CASE

The production processes were specified at different levels of detail. For example, at one site, a production process was divided into 26 activities, whereas, at another, it was divided into over 200 activities. This made the identification of which activities conducted at one site correspond to those at another problematic. The AMA4EA method created EA models of production processes at both the enterprise and site levels. This enabled the practitioners at the manufacturing company to access the specifications of the production processes at different sites through the production process at the enterprise level and vice versa. The EA model with the production process at the enterprise level is shown in Figure 26. Two examples of EA models at the site level (one for each site) are show in Figure 27.

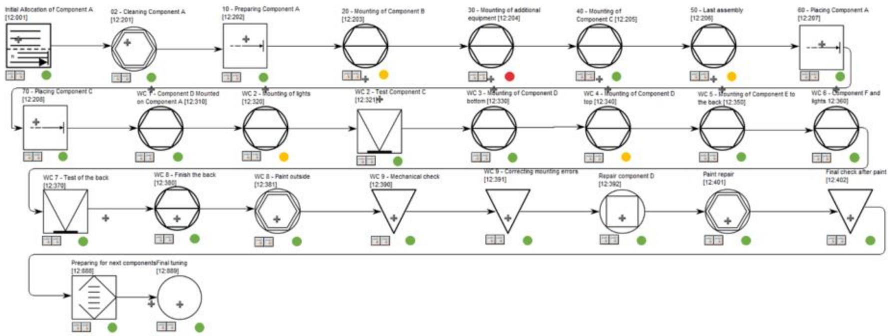


Figure 26. Production process at the enterprise level; this figure was automatically created in QualiWare's EA repository[14] *(Nardello et al. 2019b).*

[14] The aggregation of the performance measurements at the enterprise level involves the addition of the performance measurements for the activities conducted at the site level. The three levels of the performance measurements are predefined in QualiWare's EA repository as follows: value 0 “green”, values 1–3 “yellow”, and values higher than 3 “red”.

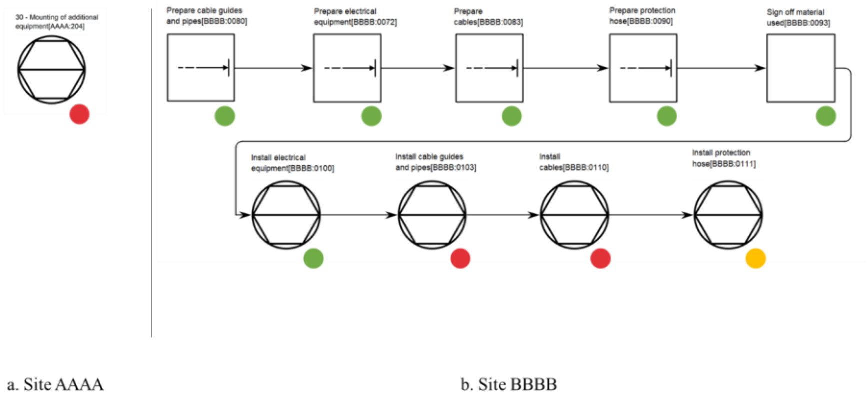


Figure 27. Production process at the site level; this figure was automatically created in QualiWare's EA repository. This example visualizes the activities involved in sub-process 30 – mounting of additional equipment (Nardello et al. 2019b).

5.4. ADDITIONAL INSIGHTS AND REFLECTIONS

The AMA4EA method was presented to Enterprise C, and data for its evaluation was gathered. In this case, the data in SAP ERP was excessively abstract and represented the production process poorly. Therefore, the extension of the AMA4EA method would have required different solutions from those developed for Enterprise B. For example, solutions that would make it possible to further detail the data in the ERP to better represent production processes were required. This approach, however, would have required the collection of additional data; as such, it was not undertaken due to the very short data collection period.

The extended AMA4EA method was presented to the Swedish manufacturing company and integration platform. They both recognized the importance of this contribution and attempted to gather data for the further evaluation and development of the method. Unfortunately, this attempt was unsuccessful, and data was never provided.

In June 2019, the author accompanied representatives from QualiWare ApS to the Gartner the Gartner Enterprise Architecture and Technology Innovation Summit in London. This event brings together EA professionals, C-level executives, and industry experts to discuss emerging topics and trends in the field of EA. The author discussed the problem of process heterogeneity with the participants at the conference to seek their suggestions for addressing this problem and to learn about their relevant experiences. A consultant from an EA repository company mentioned that he had worked on a similar case in the health sector in the US involving hospital invoice payment processes. In his project, the payment processes of all hospitals in the US needed to be aligned. His solution to the problem was to develop a high-level model of the overall process and to map the local processes to it. Although the details of the project were not shared, the concept behind the consultant's solution was similar to the solution developed in this article.

As shown in Table 8, existing automated EA modelling methods are predominately evaluated using network scanner applications. However, Farwick et al. (2016) instead used software for integrating enterprise information systems (i.e. an enterprise service bus [ESB]) and for managing the hardware and software components of an enterprise (i.e. configuration management database [CMDB]). These software packages are typically implemented and managed exclusively by an enterprise's IT functional unit. The enterprise information systems used by other functional units are therefore not used in the evaluation of existing automated EA modelling methods.
Furthermore, automated EA modelling methods that use network scanner applications are designed to operate with a specific ontology (i.e. CySeMoL). The method of Farwick et al. relates input data directly to elements in the EA repository without extending the data with an ontology. Therefore, it can be said that the AMA4EA method is the only automated EA modelling method that is designed to use data from enterprise information systems and to extend data using industry-specific ontologies.

Table 8. Data sources used to evaluate automated EA modelling methods.

Data source	**Farwick et al.** (2016)	**Buschle et al.** (2011)	**Holm et al.** (2014)	**Välja et al.** (2015)	**Välja et al.** (2016)
Configuration Management Database (CMDB)	X				
Enterprise service bus (ESB)	X				
NeXpose – Network Scanner		X	X	X	X
Wireshark – Network Scanner				X	X
Nessus – Network Scanner					X

5.5. RESEARCH CONTRIBUTION

This section summarizes the research contributions of the presented above in four parts. The first contribution is the design and evaluation of a new and innovative method for creating EA models from data. The second contribution is the use of data from enterprise information systems. The third contribution is the extension of data using ontologies. Finally, the fourth is the provided by the AMA4EA method for the management of process heterogeneity. These contributions address the lack of standardization of information in enterprise information systems, support the management of process heterogeneity, and represent an efficient modelling approach, which is required in digital manufacturing.

5.5.1. METHOD TO CREATE EA MODELS FROM DATA

AMA4EA is a method with which one can "automatically abstract detailed data from enterprise [information] systems to concepts" (Nardello et al. 2019a). The AMA4EA environment is a system for abstracting data using abstraction hierarchies. AMA4EA instantiates the abstracted data in an EA repository and automatically creates EA models (Nardello et al. 2019a). The method is divided into two phases: The preparation phase starts with a stakeholder and an architect, who jointly define the desired EA models. Thereafter, the DSM and architect are involved in the identification of data sources that may prove useful in creating the EA models. Next, the architect determines the abstraction hierarchy. Finally, the architect prepares the AMA4EA environment. The execution phase starts with the extraction of data from enterprise information systems. Data is then imported into the AMA4EA environment. The abstraction algorithm in the AMA4EA environment abstracts the data automatically. The data import algorithm imports the data and the respective abstractions thereof to an EA repository. The instantiate and position algorithm automatically instantiates elements in the EA repository with the data and respective abstraction thereof. In addition, the algorithm automatically creates the desired EA models and positions those elements in the EA repository in the EA models. The design and evaluation of this method began in article 4 and continued in articles 5 and 6. In general, the AMA4EA method was perceived as a straightforward method by the manager.

5.5.2. USE DATA FROM ENTERPRISE INFORMATION SYSTEMS

As shown in Table 8, the AMA4EA method was evaluated with data from enterprise information systems used by functional units other than IT unit. The data was extracted from ERP and MES, as these systems define production processes. Enterprises use ERP systems to manage resource planning.[15] The purpose of these systems is to integrate all of the processes needed to run enterprises (e.g. the processes of different functional units related to planning, inventory purchase, sales, marketing, finance, human resources, etc.). ERP systems contain production routing tables. These tables specify the list of activities required to manufacture a product or component in an ordered manner. Enterprises use MESs to manage production processes.[16] These systems track the execution of production processes from raw materials to finished products. In addition, they manage equipment at a production site by sharing data and

[15] https://www.investopedia.com/terms/e/erp.asp

[16] https://www.techopedia.com/definition/11847/manufacturing-execution-system-mes

communicating with that equipment. Therefore, ERPs and MESs manage data related to production processes and their execution. For this reason, the data stored on these systems has been successfully used as a source for creating EA models. The main outcome of the evaluation of the method was that the method significantly contributed to sharing data about production processes. The data was abstracted in such a manner that it could be understood by stakeholders without previous experience with these systems.

5.5.3. EXTENDING DATA WITH ONTOLOGIES

The AMA4EA method allows one to specify ontologies with which to abstract data and create EA models at different abstraction levels. The AMA4EA method was tested with the production process classification as an ontology. The data from the tables in the ERP and MES was mapped to the ontology; therefore, the AMA4EA method was used to implement an ontology of business data. This approach differs from that used by other automated EA modelling methods, which are either designed to use a very technical ontology (i.e. those that use network scanners) or do not use any ontology other than that in the EA repository.

In the comparison of the EA models with and without abstraction (Figure 24), it emerged that the latter was difficult to understand, as the data related to the production process were unclear and included very little information. In comparison, the first was a major improvement on the other model. More information can be understood when using the EA model with the ontology. The use of the ontology to abstract the data made the process understandable to people who have not worked with these specific systems before.

5.5.4. MANAGING PROCESS HETEROGENEITY

The original AMA4EA method was extended to address process heterogeneity. The extended AMA4EA is a method that addresses the process heterogeneity problem by creating EA models with overviews and EA models with the details of production processes. The demonstration using data from a Danish international manufacturing company shows that the extended AMA4EA method can support the management of process heterogeneity. The method automatically creates an overview model that enables production managers to access information on production processes at different sites.

CHAPTER 6. USING DATA TO ENHANCE EA MODELS FOR DIGITAL MANUFACTURING

This chapter presents the research related to the third thesis objective. Articles 2, 3, and 6 are summarized by presenting their respective research questions and content. Articles 2 and 3 enhanced the EA models to provide operational support, whereas article 6 presented the extended AMA4EA method to automate the enhancement of EA models. Following the summaries of each article, additional insights and reflections concerning the articles are presented. Finally, the contributions of the articles are summarized to address the research questions at the level of this thesis' objectives. This summary is then synthesized in Chapter 7.

This chapter presents the articles relevant to the following research question:

> How are EA models for digital manufacturing enhanced using additional data and information stored on different enterprise information systems?

Articles 2 and 3 began the process of addressing this research question by enhancing EA models with different types of data and information. Subsequently, article 6 extended the AMA4EA method to automate these enhancements and to address the problem of data heterogeneity.

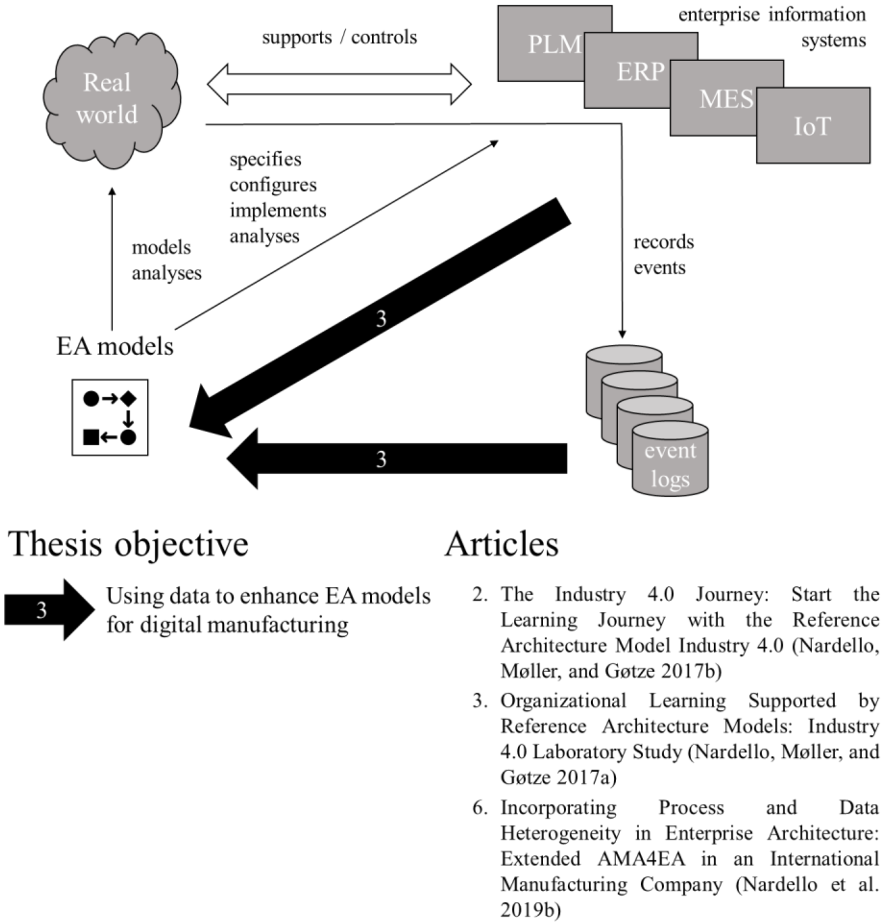


Figure 28. Theoretical framework for the third thesis objective.

6.1. ARTICLES 2 AND 3

For this objective, articles 2 and 3 both investigated the following research questions:

> How are EA models for digital manufacturing enhanced to include manufacturing documentation?
>
> How are EA models for digital manufacturing enhanced to include data about the status of manufacturing products and processes?

Articles 2 and 3 began addressing these research questions by enhancing EA models with data and information from different enterprise information systems. Solution 1 used error data from the learning factory's MES to change the colour of the elements in an EA model. This solution alerted the learning factory manager of a problem in the production process. Solution 2 involved linking external documents from the university’s project database to elements in an EA model. This solution shared instructional videos, other project reports, and technical documentation through an EA model.

6.1.1. SOLUTION 1

To address the need to provide operational support, MES data and information about the learning factory were included in the EA models. Information concerning production errors was visualized in the form of a process model. Data stored in a table in the MES was used to change the colour of the elements in the models when it was necessary to signal a problem in the production process. Figure 29 presents an example of the process before (Figure 29a) and after (Figure 29b) the error occurred, as well as the tables in QualiWare’s EA repository that provided the detailed information (Figure 29c and d).

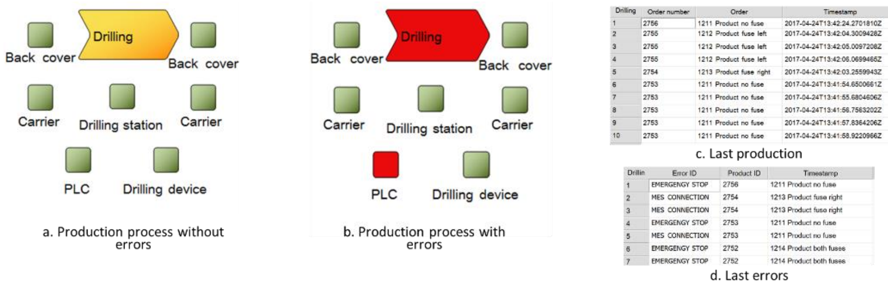


Figure 29. Signalling an error in an activity in the production process (Nardello, Møller, and Gøtze 2017b).

6.1.2. SOLUTION 2

To provide further operational support, the second solution was developed to share reports and other documents through EA models. This solution linked external documents to the elements in the EA models. Figure 30 shows how a video, other students’ reports, and technical documentation are shared through an EA model.

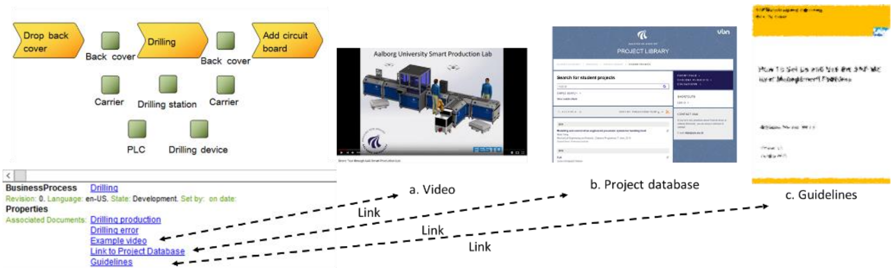


Figure 30. Documentation linked to the elements in an EA model (Nardello, Møller, and Gøtze 2017b).

6.1.3. EVALUATION

The contributions of the solutions presented above to organizational learning and to the information dissemination sub-process were assessed during an interview with the learning factory manager. The main contributions were as follows:

- The solutions provided access to data and information related to the learning factory (e.g. technical documentation).
- Solution 1 helped the manager to solve errors in the production process more efficiently.
- Solution 2 was important in disseminating information and operational support. For each element in the EA models, there are linked documents that explain what the modules in the learning factory can be used for.
- Solution 2 provides students with easy access to information.

6.2. ARTICLE 6

In articles 2 and 3, documentation and data were manually added to the EA models, which proved extremely time-consuming. To address this problem, the following research questions were investigated:

> How to further develop automated EA modelling methods that model business aspects to include documentation in EA models?
>
> How to further develop automated EA modelling methods that model business aspects to include performance measurements in EA models?

The research for these articles was undertaken to address the data heterogeneity problem experienced in the empirical context. The international manufacturing company that participated in this article used the production process at the site level in its ERP to structure the collection of data from the production process and assembly documentation. The article refers to both external resources as data and documentation about manufacturing processes, resources, or products. Since the processes at the site level are heterogeneous, the data is also heterogeneous and is therefore difficult to share and compare. Production managers lacked "a system that collects production process data and external resources in a system that relates these data with an overview of production processes and the detailed production processes (i.e. at the site level)" (Nardello et al. 2019b). At the company, different systems are used to store production data, which requires production managers to access data separately. This is problematic because "fragmented data hinders international manufacturing companies from using this data effectively and efficiently to improve production processes" (Nardello et al. 2019b).

6.2.1. EXTENDED AMA4EA FOR DATA HETEROGENEITY

To automate the enhancement of EA models and address the data heterogeneity problem, the AMA4EA method was extended to include performance measurements and assembly documentation in the generated EA models. Performance measurements are included through a database query, while documentation is accessed through uniform resource locators (URLs). An example of a performance measurement is the number of errors associated with each activity at the site level during a week. This performance measurement aggregates the number of errors reported for each activity at the site level to the sub-processes at the enterprise level. This solution enables the comparison and improvement of performances and processes at different sites. To implement this solution, the activities in the preparation and execution phase of the AMA4EA method were extended as shown in Table 9 and Table 10.

Table 9. The extensions of the four activities in the preparation phase of the AMA4EA method for incorporating data heterogeneity (Nardello et al. 2019b)

Activity	**Description of AMA4EA**
1. Define the desired EA model	The stakeholder and the architect acknowledge the need to include external resources in the EA models at two levels of detail. This requires defining the external resources relevant for the purpose, scope, and concepts at each level (e.g. KPIs or documentation). In addition to choosing the type of EA model, the stakeholder and the architect determine how the external resources will be visualized for each level. For instance, KPIs can be visualized with colour coding, and different documentation can have different icons in the EA models. These visualizations can be different for the two levels. *Input:* The stakeholder describes how the problem can be addressed with EA models that include external resources. *Output:* Definition of the desired EA models, including the external resources and their visualization.
2. Identify data sources	The DSM identifies the ESs used to manage the external resources to be included in the desired EA model and the location of data on these ESs. For example, assembly documentation can be accessed through URLs, and the data required for the KPIs can be accessed through a database query. *Input:* Definition of the desired EA models, including the required external resources. *Output:* Names of the ESs with the relevant data and the URLs or queries required for extracting the data.
3. Identify abstraction hierarchy	(No extension is necessary).
4. Set up the AMA4EA environment	For both the “main” and “site” interfaces, the structural metadata of the AMA4EA environments is extended with one column for each external resource. These columns store the URL or query required for accessing the external resource. For instance, one column can store URLs for accessing assembly documentation, while another column can store database queries required to retrieve performance measurements. *Input:* AMA4EA environment with “main” and “site” interfaces *Output:* AMA4EA environment with “main” and “site” interfaces, with the columns for storing the URLs and queries required to access external information.

Table 10. The extensions of the three activities in the execution phase of the AMA4EA method for incorporating data heterogeneity (Nardello et al. 2019b)

Activity	Description of AMA4EA
1. Extract data from ES to the AMA4EA environment	Following the extraction of data from the ESs to the AMA4EA environment, the DSM inserts the queries and URLs necessary to access external resources into the dedicated columns created in the setting up of the AMA4EA environment activity. *Input:* Name of the ESs with the relevant data and the URL or query required for extracting the data. *Output:* AMA4EA environment with the URLs and queries required in the "main" and "site" interfaces to access external resources.
2. Abstract data in the AMA4EA environment	(No extension is necessary).
3. Create the desired EA model	The *instantiate and position algorithm* stores the queries and URLs required to access external resources in elements in the EA repository. During the instantiation of the elements in the EA models, the URL for each element is visualized using a predefined symbol. In addition, if the queries return numerical results, they are visualized for each element. This visualization can be enhanced by the use of predefined colour schemes. *Input:* AMA4EA environment with data from the ESs in the "main" and "site" interfaces, including the URLs and queries required to access external resources. *Output:* Enterprise architecture models with elements that provide access to external resources and visualize performance measurements.

6.2.2. EMPIRICAL CASE

The extended AMA4EA method created an EA model at the enterprise level with 26 activities (Figure 26) and was used to specify activities at the site level with EA models (Figure 27). To link data and documentation to the elements in the EA models, SQL queries and URLs were used. An example of an SQL query for retrieving the data required for measuring the number of errors reported by at an activity in the production process is the following:

```
select count(*) from BBBB.tblErrors where (Activity = 0072)
and (DateTimes <= Date()) and (DateTimes >= (Date() - 7));
```

An example of an URL used to retrieve the assembly documentation of an activity at the site level is the following:

```
https://man-my.sharepoint.com/:f:/g/BBBB/0072
```

Further details about the method and EA models are included in the article.

6.3. ADDITIONAL INSIGHTS AND REFLECTIONS

The solutions for including additional data and information in EA models rely on the existence of unique IDs for a production site and the activities involved in production processes that are used across enterprise information systems (i.e. production plan BBBB and activity 0072 are used to access documentation concerning an activity). However, this approach may not be possible in other enterprises. Therefore, a more robust solution for including additional data and information needs to be developed in the future.

The performance measurements used in the article are simplified. Future work should address this limitation by developing performance measurements based on industry standards (e.g. (ISO 2011)).

During the presentation of the extended AMA4EA method to manufacturing companies, they raised the point that this method could be used to identify data quality problems and gaps in their enterprise information systems. Therefore, should this method produce poor EA models, these could be used to identify where the data should be improved.

The production process classification was extremely useful, but it is not an ontology, as it lacks properties and attributes of the elements in the classification. This point is further discussed in Section 7.2.3.

6.4. RESEARCH CONTRIBUTION

This section summarizes the research contributions presented in this chapter in three parts. The first contribution is the use of the enhanced EA models to provide operational support. The second contribution is the design and evaluation of a novel and innovative method for enhancing EA models with data and information. Finally, the third contribution is the support for managing data heterogeneity. The EA models created with the AMA4EA method are presented in Section 5.2.2.

6.4.1. ENHANCED EA MODELS TO PROVIDE OPERATIONAL SUPPORT

To provide operational support, the EA models were enhanced to include documentation and data. In articles 2 and 3, two solutions included error data from the MES in an EA model and featured links to documents and instructional videos in the EA model. The enhanced EA models informed the learning factory manager of problems in the production process and provided him with the documentation required to address these issues.

6.4.2. METHOD TO ENHANCE EA MODELS OF THE BUSINESS ASPECT WITH DATA AND INFORMATION

The AMA4EA method was extended to include documentation and performance measurements at two levels of detail, namely site and enterprise. To be more specific, the AMA4EA environment and the activities in the two phases of the method were extended. In this way, it was possible to link documentation, (e.g. that relating to assembly), to the elements in the EA models created by AMA4EA. This extension enabled the comparison and improvement of the performance of production processes at different sites.

6.4.3. MANAGE DATA HETEROGENEITY

The contribution to managing data heterogeneity lies in the creation of an artefact that collects data from different enterprise information systems, aggregates that data into an overview based on its level of detail, and provides access to the low-level data. In more detail, the extended AMA4EA method abstracts data in two ways: (1) through the creation of EA models at two levels (enterprise and site) and (2) through the inclusion of production process data and documentation (e.g. performance measurements) in the EA models. The extended AMA4EA method supports managing data heterogeneity by enhancing EA models at the enterprise and site levels with documentation and performance measurements from different sites. Enterprise architecture models at the two levels facilitate access to the data and documentation stored on different enterprise information systems. Furthermore, the EA models enable the comparison of performance measurements based on heterogeneous processes and data. The evaluation of the extended AMA4EA method with data from a Danish international manufacturing company demonstrated that the extended AMA4EA method addresses the data heterogeneity problem. It facilitates the sharing and comparison of performance measurements and documentation of different sites and aggregates data in the EA model at the enterprise level.

CHAPTER 7. SYNTHESIS OF THE RESEARCH CONTRIBUTIONS

This chapter synthesizes the research contributions presented in Chapters 4, 5, and 6. For each of the research objectives, the contributions are synthesized in the form of design process artefact and a design product artefact. These artefacts are evaluated and discussed in Chapter 8 based on the research gaps identified in Chapter 2 and research design presented in Chapter 3.

The purpose of this thesis is to explore the development of EA models as digital models for digital manufacturing and the enhancement of EA models to provide the operational support required to enhance manufacturing products and processes. The overall research questions of the thesis are as follows:

> Which EA models can be used as digital models for digital manufacturing?
>
> How are EA models created and enhanced with data and information from different enterprise information systems?

Figure 31 frames this thesis' objectives and their contributions to the theoretical framework described in Chapter 2. In addition, for each objective, the manufacturing challenges and digital manufacturing requirements, as well as the empirical context for the evaluation of each contribution, are reported (the numbering in the figure should prove helpful).

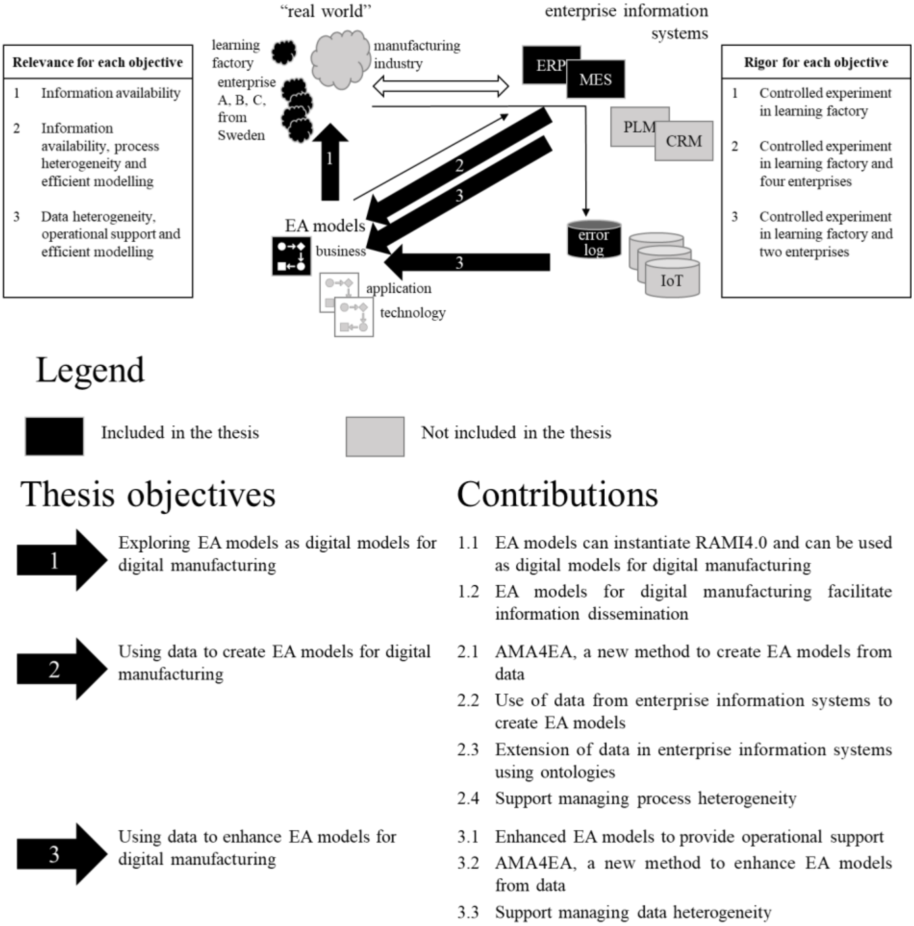


Figure 31. Research contributions and their relevance and rigor presented within the theoretical framework.

7.1. EXPLORING EA MODELS AS DIGITAL MODELS FOR DIGITAL MANUFACTURING

Enterprise architecture models are important for the design of an enterprise. As described in Section 2.4, the first thesis objective explored the applicability of EA models as digital models for digital manufacturing. The research conducted to achieve this objective required addressing the information availability challenge. More specifically, it was necessary to address the difficulty of accessing the information stored on enterprise information systems and manufacturing companies' employees' lack of understanding of resources and processes.

As explained in Section 3.4, the research for this objective was primarily conducted in an artificial context, namely the learning factory. This research involved the learning factory manager and practitioners from the MADE manufacturing companies.

7.1.1. EA MODELS CAN INSTANTIATE RAMI4.0 AND CAN BE USED AS DIGITAL MODELS FOR DIGITAL MANUFACTURING

Enterprise architecture models can be used to model digital manufacturing. Chapter 4 presented the seven EA models used to instantiate RAMI4.0 at the learning factory. These EA models covered all RAMI4.0 architecture layers. In addition, Chapter 4 presented the approach, which was both top- and bottom-down, used to instantiate RAMI4.0. Furthermore, EA models were applied to model manufacturing processes. As presented in Chapter 4, EA models were used to document the manufacturing processes of the learning factory and MADE manufacturing companies.

Enterprise architecture models can be used to model smart products. Smart products can consist of physical, connectivity, and smart components (Porter and Heppelmann 2014, 67). Enterprise architecture models are suitable for modelling all of the components of smart products. As presented in Chapter 4, EA models were used to instantiate all of the architecture layers of RAMI4.0. Although it was feasible to apply EA models, some elements in the architecture layers of RAMI4.0 were partially modelled. In addition, the research in Chapter 4 was based on one reference architecture model for digital manufacturing. Alternatives were preliminarily analysed but not instantiated.

7.1.2. EA MODELS FOR DIGITAL MANUFACTURING FACILITATE INFORMATION DISSEMINATION

Enterprise architecture models for digital manufacturing facilitate information dissemination by structuring information. These EA models addressed the challenge of accessing data and information by providing the manager with up-to-date and relevant information about the learning factory. In addition, the EA models are artefacts that support the collection of new information.

Enterprise architecture models for digital manufacturing facilitate information dissemination by explaining production processes, products, and resources to new staff. In addition, they help managers to understand the relationships among products, equipment, process, components.

Design product artefact

The research contribution associated with the first objective focused on the design product artefact. The process for developing the EA models was described to support the explanation of the design product artefact. The design product artefact is the collection of EA models that instantiated RAMI4.0 and were used as digital models for digital manufacturing to facilitate information dissemination.

7.2. USING DATA TO CREATE EA MODELS FOR DIGITAL MANUFACTURING

Digital manufacturing relies on the use of data and information. Chapter 5 focused on the second thesis objective. It investigated the use data from enterprise information systems to create EA models for digital manufacturing. As presented in Section 2.4, three research gaps needed to be addressed to achieve the second thesis objective: (1) the lack of automated EA modelling methods for creating EA models related to all aspects, especially the business aspect; (2) the lack of automated EA modelling methods that use enterprise information systems as data sources; (3) and the lack of automated EA modelling methods for addressing process heterogeneity. To achieve the second thesis objective, several challenges encountered by practitioners needed to be addressed: first, the information availability challenge related to the lack of standardization of information; second, the process heterogeneity challenge; and, third, the digital manufacturing need for efficient modelling approaches. As explained in Section 3.4, the research for this objective was conducted in artificial contexts, namely at the learning factory and four enterprises. It involved the learning factory manager and practitioners from enterprises A, B, C, and the Swedish manufacturing company and integration platform. The data used was obtained from both the learning factory and industry.

7.2.1. AMA4EA, A NEW METHOD FOR CREATING EA MODELS FROM DATA

AMA4EA is a method that allows one to “automatically abstract detailed data from enterprise [information] systems to concepts” (Nardello et al. 2019a). It addresses the first two research gaps as well as the first and third practitioner challenges. The method involves some manual activities in the preparation phase and algorithms in the execution phase. For each phase, the activities and algorithms were previously explained in detail. The method was demonstrated by using ERP and MES data to create EA models of the business aspect. The learning factory manager considered the method usable and the EA models useful in understanding production processes.

The AMA4EA method can be used to create process models, and it could also be applied to other EA models of the business aspect, for example those related to product architecture. Furthermore, the AMA4EA method could be applied to create EA models related to the application and technology aspects. However, while it could potentially be applied for both of these cases, this was not demonstrated.

7.2.2. USE OF DATA FROM ENTERPRISE INFORMATION SYSTEMS TO CREATE EA MODELS

The AMA4EA method was demonstrated with data from two enterprise information systems, ERP and MES. The ERP system includes tables that specify the ordered list of activities of manufacturing processes, while the MES manages these manufacturing processes by tracking their execution and managing resources at the production site. Therefore, both systems manage data related to production processes and their execution. The AMA4EA method used these systems as data source for creating EA models.

However, other data sources for the creation of EA models were considered but not used. With regard to production processes, an IoT platform that collects data from production sites could be used to create EA models. Furthermore, other enterprise information systems (e.g. product lifecycle management and customer relationship management systems) could be used to create and enhance EA models.

7.2.3. EXTENSION OF DATA IN ENTERPRISE INFORMATION SYSTEMS USING ONTOLOGIES

The AMA4EA method creates a standardized representation of the data stored on enterprise information systems. This was achieved using ontologies to abstract data and create EA models at different abstraction levels. The AMA4EA method was tested with the production process classification as an ontology. The data from the tables in the ERP and MES was mapped to the ontology. The comparison of the EA model with and without ontology (Figure 24) demonstrated that the standardized representation was a major improvement from the non-standardized one, and that the information in the EA model was understandable by stakeholders without previous experience with the systems used.

The production process classification includes concepts related to EA models related to the business aspect. Other ontologies and data could be used to evaluate AMA4EA. Although the classification proved to be extremely useful, it is not an ontology, as it lacks definitions of the properties of entities and their relationships. Ontologies related to manufacturing processes could be applied (Backhaus and Reinhart 2017; Järvenpää, Lanz, and Siltala 2018; Järvenpää et al. 2019).

7.2.4. SUPPORT MANAGING PROCESS HETEROGENEITY

Enterprise architecture models can be used to address process heterogeneity. Process heterogeneity makes identifying which activities at one site correspond to those at another problematic. There is a lack of an overview of production processes that could assist in managing process heterogeneity. As described in Section 5.5.4, the extended AMA4EA method was used to create EA models that provide overviews and describing the details of production processes. This method was evaluated using data from two MADE manufacturing companies. The demonstration showed how an overview model that enabled production managers to access information on production processes at different sites was created. It is possible to access the specifications of the production processes at different sites through the production process at the enterprise level and vice versa.

Although these EA models were the results of several interactions with manufacturing companies, the final EA models were not evaluated after they were created. In addition, it is important that they be further evaluated by applying them to other cases of process heterogeneity.

Design process artefact and design product artefact

The research contributions for the second objective include both a design process artefact and a design product artefact. The design process artefact is the AMA4EA method (including the extended AMA4EA), which uses and extends with ontologies heterogeneous data from different enterprise information systems to create EA models pertaining to the business aspect at different levels of abstraction.

The design product artefact is the collection of EA models (i.e. process models) created during this research, which relate and visualize heterogeneous processes at different abstraction levels (i.e. enterprise and site).

7.3. USING DATA TO ENHANCE EA MODELS FOR DIGITAL MANUFACTURING

To provide the operational support required to enhance manufacturing processes and products, EA models need to be enhanced with data and information. Data and information from enterprise information systems and event logs can be used for this purpose. As presented in Section 2.4, There is a lack of an automated EA modelling method that includes in EA models additional data and information from multiple sources. The research conducted to address this gap needed to identify an efficient modelling approach and address the data heterogeneity challenge. As explained in Section 3.4, the research for this objective was conducted in artificial contexts, namely the learning factory and two enterprises. It involved the learning factory manager and practitioners from enterprises B and C. The data used was obtained from both the learning factory and these enterprises.

7.3.1. ENHANCED EA MODELS TO PROVIDE OPERATIONAL SUPPORT

The EA models developed for the instantiation of RAMI4.0 were enhanced to include documentation and data from different enterprise information systems. As described in Section 6.4.1, two solutions that included error data from an MES in an EA model and include links to relevant instructional videos and documentation were created. The enhancement of EA models allowed them to inform the learning factory manager of problems in the production process and provided him with the documentation required to address such problem. In this way, they provided operational support.

7.3.2. AMA4EA, A NEW METHOD TO ENHANCE EA MODELS FROM DATA

The extended AMA4EA method enhances EA models by extending them to include data and information from different enterprise information systems. As summarized in Section 6.4.1, the extended AMA4EA method includes documentation and performance measurements in EA models at two levels of detail (enterprise and site). The extension links assembly documentation and performance measurements to the elements in the EA models created by AMA4EA. Combined with the extension for addressing process heterogeneity, it enables the comparison and improvement of the performances of production processes across different sites.

The extended AMA4EA method was developed with one performance indicator, which was defined by one enterprise. The method could be extended to include other performance indicators from other enterprises or industry standards (ISO 2011).

7.3.3. SUPPORTING MANAGING DATA HETEROGENEITY

Data heterogeneity makes sharing and analysing data that is managed by different enterprise information systems problematic. As described in Section 6.4.3, EA models that included data and documentation stored on different enterprise information systems were developed. Performance measurements and documentation concerning different sites were included in the EA models. In addition to providing access to documentation, these EA models enabled the comparison of performance measurements of heterogeneous processes and data at an international manufacturing company. This demonstrates how data heterogeneity can be addressed using EA models.

Although these EA models were the results of several interactions with manufacturing companies, the final EA models were not evaluated after they were created. In addition, it is important that further evaluations with other cases of process heterogeneity be conducted.

Design process artefact and design product artefact

The research contributions for the third objective include both a design process artefact and a design product artefact. The design process artefact is the extended AMA4EA method, which uses heterogeneous data from different enterprise information systems to enhance EA models pertaining to the business aspect at different levels of abstraction.

The design product artefact is the collection of enhanced EA models created and developed in the course of the research conducted for this dissertation, which provide operational support and relate and visualize heterogeneous data and information at different levels of abstraction (enterprise and site).

CHAPTER 8. DISCUSSION

This chapter evaluates the research contributions synthesized in Chapter 7. Thereafter, it discusses the significance, implications, and limitations of these research contributions. Finally, future research directions and reflections on the research conducted for this dissertation are presented.

The purpose of this thesis is to explore the development of EA models as digital models for digital manufacturing and to enhance EA models to provide the operational support required to enhance manufacturing products and processes.

8.1. EVALUATION OF RESEARCH CONTRIBUTIONS

This evaluation is based on the content of Chapter 3.

8.1.1. RESEARCH RELEVANCE

This section discusses the research relevance of the contributions of this thesis. This discussion is based on the discussion about research relevance in Section 3.3.2. For each of this thesis' objectives, both existing problems encountered by manufacturing companies and research topics relevant to future research were considered. Using field notes, the problems encountered by manufacturing companies, as well as relevant information, were identified and organized. Using this approach, it was possible to undertake research that aimed at addressing these problems and contributed to the identification of intriguing topics for future research (e.g. Industry 4.0).

8.1.2. RESEARCH RIGOR

This section discusses the research rigor of the research contributions of this thesis. This discussion is guided by Table 11, which presents the results of the evaluation based on the framework presented in Section 3.4.1, Table 2. For each research objective, the results of the evaluation are first presented and then discussed.

Table 11. Results of the evaluation of the research contributions of the thesis.

Thesis Objective and Contributions	Design Process or Design Product	Contribution Type	Generalizability Level	Naturalistic or Artificial	Ex Ante or Ex Post	Criteria
1. Exploring EA models as digital models for digital manufacturing						
The collection of EA models that instantiated RAMI4.0 were used as digital models for digital manufacturing that facilitate information dissemination.	Product	Exaptation	Level 1	Artificial, Lab Experiment	Ex Post	Feasibility, Usefulness and Applicability
2. Using data to create EA models for digital manufacturing The AMA4EA method (including the extended AMA4EA) uses and extends with ontologies heterogeneous data from different enterprise information systems to create EA models pertaining to the business aspect at different levels of abstraction.	Process AMA4EA	Improvement	Level 1 and towards level 2	Artificial, Lab Experiment	Ex Post	Usefulness, Usability and Efficiency
	Extended AMA4EA			Artificial, Field Experiment	Ex Post	Feasibility and Applicability
The collection of EA models (i.e. process models) created that relate and visualize heterogeneous processes at different abstraction levels (i.e. enterprise and site).	Product	Improvement	Level 1	Artificial, Lab and Field Experiment	Ex Post	Feasibility and Applicability
3. Using data to enhance EA models for digital manufacturing The extended AMA4EA method uses heterogeneous data from different enterprise information systems to enhance EA models pertaining to the business aspect at different levels of abstraction.	Process Extended AMA4EA	Improvement	Level 1 and towards level 2	Artificial, Computer simulation	Ex Post	Feasibility and Applicability
The collection of enhanced EA models developed and created provide operational support and relate and visualize heterogeneous data and information at different abstraction levels.	Product	Improvement	Level 1	Artificial, Lab Experiment	Ex Post	Feasibility and Applicability
				Computer simulation		

8.1.2.1 Exploring EA models as digital models for digital manufacturing

The first objective of this thesis was to explore the use of EA models as digital models for digital manufacturing. Table 2 summarizes the aim for the evaluation of the research contributions, while Table 11 presents the results of the evaluation. This first contribution focused on a design product artefact.

Contribution type of the design product artefact

Aligned with Table 2, this artefact was the result of the application of a known solution (i.e. EA models) to the novel concept of applying digital models for digital manufacturing. Therefore, EA models from the EA discipline were applied in manufacturing and operations management. However, it must be noted that while existing solutions in manufacturing and operations management (i.e. production layout models, computer-aided process planning, or group technology) were considered, they were not thoroughly investigated.

Generalizability level of the design product artefact

This contribution aimed at generalizability levels 1 and 2, but it resulted in a specific instantiation of the artefact (i.e. level 1). It instantiated QualiWare’s EA models, but it did not explain why and under which conditions the artefact works. Without this explanation, this artefact is not sufficiently abstract to be considered a level 2 contribution.

Naturalistic or artificial evaluation of the design product artefact

In contrast to the evaluation context presented in Table 2, the design product artefact was evaluated in an artificial context. A laboratory experiment was undertaken in the learning factory, and the learning factory manager was interviewed.

Ex ante or ex post evaluation of the design product artefact

As specified in Table 2, the evaluation of the artefact occurred only after it was developed (i.e. ex post), not prior to its development (i.e. ex ante).

Criteria of the design product artefact

The evaluation criteria listed in Table 2 were feasibility, usefulness, and applicability. The development and instantiation of the artefact proved its feasibility in terms of the aspects that it addressed. As mentioned in Section 4.4, the EA models did not fully instantiate some layers of RAMI4.0. The purpose of the artefact was to demonstrate that EA models can serve as digital models that represent manufacturing products, processes, components, and resources, as well as their use for communicating data and information about digital manufacturing. The learning factory manager confirmed that this purpose was achieved. With regard to the applicability of the artefact, the degree to which it could be applied in different contexts was not evaluated because such contexts were not identified.

Discussion

The differences between the aimed evaluation and its results presented respectively in Table 2 and Table 11 were primarily due to research design decisions and the empirical context. With regard to the empirical context, the inability to develop the EA models in naturalistic contexts significantly limited the applicability of the artefact. This inability, combined with the initial satisfaction with the artefact, resulted in the research design decision to address the second thesis objective. Alternatively, a more thorough investigation intended to explain why and under which conditions the artefact works could have been undertaken to increase the generalizability level to 2. As another alternative, a more thorough analysis of existing solutions in manufacturing and operations management for the use of digital models in digital manufacturing could have been undertaken.

8.1.2.2 Using data to create EA models for digital manufacturing

The second objective of this thesis was to use data to create EA models for digital manufacturing. Table 2 summarizes the aim of the evaluation of the research contributions, while Table 11 presents the results of the evaluation. The design process artefact and the design product artefact are the results of two iterations. The first artefact was produced in the learning factory context, while the second was created in the context of the two MADE manufacturing companies.

Contribution type of the design process artefact

As stated in Table 2, the design process artefact was expected to be an improvement because it creates EA models pertaining to the business aspect, an aspect that other automated EA modelling methods do not address. In doing so, it improves automated EA modelling methods by using ontologies to extend data from different enterprise information systems. This improvement enables the creation of EA models at different levels of abstraction.

Generalizability level of the design process artefact

The design process artefact aimed at achieving generalizability levels 1 and 2. The artefact was instantiated (i.e. level 1), and the articles provided an initial explanation of why and under which conditions the artefact works (i.e. a step towards achieving level 2). The method was described at a level that allows it to be applied in different contexts. Furthermore, the articles explained that the artefact works because it uses data that defines the elements of an enterprise (e.g. a production routing table that specifies a production process) to create an EA model that represents the production process. Furthermore, the artefact works when the data that defines the elements of the enterprise is correct, at the right level of detail, and can be extracted from the enterprise information system.

Naturalistic or artificial evaluation of the design process artefact

In contrast to the planned evaluation context, this artefact was evaluated in two artificial contexts. First, it was evaluated through a laboratory experiment in the learning factory involving the learning factory manager. Second, it was then evaluated by means of a field experiment conducted at two MADE manufacturing companies. This approach made it possible to collect industrial data to be used in experimentation with the method.

Ex ante or ex post evaluation of the design process artefact

In both iterations, an ex post evaluation was undertaken.

Criteria of the design process artefact

To go into more detail concerning the evaluation of the artefact, the two iterations were evaluated separately. In the first iteration, the evaluation was performed with the learning factory manager. This evaluation focused on the usefulness, usability, and efficiency of the artefact. The first criteria has two perspectives: usefulness for achieving a predetermined research purpose and practitioner purpose. In the first case, the artefact addressed a research gap (i.e. the inability of automated EA modelling methods to create EA models pertaining to the business aspect). In the second case, the artefact addressed a practice problem (i.e. information is not standardized and therefore is difficult to understand and use). When evaluating the usefulness of the artefact in terms of the research purpose, the learning factory manager confirmed that the AMA4EA method created EA models pertaining to the business aspect using data from the facility's ERP and MES. When evaluating the usefulness of the method in terms of the practice problem, the learning factory manager declared that the artefact was useful since it abstracted data from two enterprise information systems in manner that was understandable by stakeholders without previous experience with these systems. Furthermore, when evaluating the usability of the artefact, he stated that he could have executed the AMA4EA method by himself. However, this was only a superficial evaluation of the usability of the artefact, as the learning factory manager did not apply the method.

Based on the requirement that the artefact needed to offer an efficient modelling approach, Table 2 also included efficiency as a criteria. This implied a comparison between a manual method and the AMA4EA method. This comparison was undertaken because it was decided that the empirical context of the learning factory would not have produced reliable results.

In the second iteration, the evaluation was performed using data from two MADE manufacturing companies; it focused on the feasibility and applicability of the artefact. In evaluating the feasibility of the method, the author demonstrated the execution of the artefact and that the extended AMA4EA method created EA models at both the enterprise and site levels using data of heterogeneous processes from the ERP system of the case company. In evaluating the applicability, the author demonstrated that the AMA4EA method and the extended AMA4EA method can be applied with data from different environments (i.e. those of the learning factory and one manufacturing company).

Contribution type of the design product artefact

The design product artefact was a result of the application of the design process artefact. As described in Table 2, this artefact was expected to support the other artefact without being an important contribution in itself.

Generalizability level of the design product artefact

This artefact did not aim at specific generalizability levels. However, it could be argued that the instantiation of the artefact is at level 1. The functioning of the artefact was demonstrated in the articles.

Naturalistic or artificial evaluation of the design product artefact

Both iterations of the artefact were undertaken in an artificial context. The first was evaluated in a laboratory experiment conducted at the learning factory, whereas the second was tested in a field experiment at two MADE manufacturing companies.

Ex ante or ex post evaluation design of the product artefact

In both iterations, an ex post evaluation was undertaken.

Criteria of the design product artefact

As for the previous artefact, this artefact was also the result of two iterations and two evaluations. In the first iteration, the evaluation conducted with the learning factory manager focused on the usefulness and feasibility of the artefact. It resulted in the recognition of the fact that the use of an ontology and its notation represented an improvement on the business process modelling notation. The EA model using the latter was difficult to understand and included very little information; the former was a major improvement and communicated more information in a more understandable way. The EA model created using the ontology and its notation standardized the information stored on enterprise information systems and therefore made that information available. The feasibility of the artefact was demonstrated by the author's creation of this artefact. However, while this contribution is an improvement on the business process modelling notation, it does not take into consideration other artefacts that may also have contributed to improving the business process modelling notation. In the second iteration, the ex post evaluation used data from two MADE manufacturing companies; it focused on the feasibility and applicability of the artefact. The feasibility was demonstrated by creating EA models at the enterprise and site levels using data concerning heterogeneous processes obtained from the ERP system of one company. The applicability was demonstrated by the creation of EA models at both the learning factory and one MADE manufacturing company.

Discussion

The differences between the aimed evaluation and its results presented respectively in Table 2 and Table 11 had four main impacts on the rigor of the research presented in this thesis.

First, the inability to evaluate the artefacts for the second objective in a naturalistic context limits the research rigor. However, in contrast to the artefact for the first objective, in this case, it was possible to collaborate with manufacturing companies. It was thus possible to access real systems and real people, but not real problems (i.e. real tasks in real settings). Data from the enterprise information systems of two MADE manufacturing companies was gathered, and several meetings were held with these companies. However, the second iteration of the artefacts was not evaluated. To address real problems, real tasks (i.e. managing process heterogeneity across production sites) conducted in real settings (i.e. in the offices and with the employees of these manufacturing companies) were required. It was not possible to engage with real tasks for three main reasons: First, although process heterogeneity is a challenge, the manufacturing companies might have not been addressing it at the time of the research. In the two MADE manufacturing companies, no evidence was found that this challenge was being addressed. Second, the research timeline restricted the author's ability to collaborate with these companies. The data for the second iteration was gathered during the winter break of 2018/2019 between the author's two stay abroad experiences in Stockholm. Article 6 was written during the second stay abroad period, and this conflicted with the period set aside for the evaluation in naturalistic contexts. Third, undertaking a naturalistic evaluation would have required QualiWare's EA repository to be usable at the case company. In addition to the time required, this would have required extensive negotiations, which were not possible due to time constraints.

Second, the evaluation of the first iterations of the artefacts involved only the learning factory manager, and therefore further evaluation with other qualified people would have significantly improved the rigor of the evaluation.

Third, ex ante evaluations concerning the soundness of the design of the artefact could have been undertaken during the second iteration of the artefacts had the designs of the artefacts been developed in time. During the meetings, new practice problems emerged, but time constraints meant that it was not possible to redesign the artefact to address these problems. Furthermore, the ex post evaluation of the second iteration involved criteria that could be assessed by the author, but it did not involve the MADE manufacturing companies. This aspect further reduces the research rigor of this contribution.

Fourth, the notation of the ontology resulted in an unexpected contribution: It improved the design product artefact created by standardizing information in enterprise information systems and making it available.

8.1.2.3 Using data to enhance EA models for digital manufacturing

The third objective of the thesis was to use data to enhance EA models for digital manufacturing. Table 2 summarizes the aim of the evaluation of the research contributions, while Table 11 presents the results of the evaluation. This contribution includes a design process artefact and a design product artefact. The former artefact is the result of a single iteration in collaboration with two MADE manufacturing companies.

Contribution type of the design process artefact

As expected, this artefact resulted in an improvement. While creating the artefact, it enhanced EA models including additional data and information. This additional data and information is not included in other automated EA modelling methods. This improvement enables the comparison of data and information in EA models at different levels of abstraction.

Generalizability level of the design process artefact

This artefact aimed at generalizability levels 1 and 2. The artefact was instantiated (i.e. level 1), and the article explained why and under which conditions the artefact works (i.e. towards level 2). The method was described at a level that allows it to be applied in different contexts. The artefact uses data and information related to the elements of an enterprise (e.g. quality performance measurements or assembly documentation for an activity in a production process) to enhance those elements in the EA model by representing the relevant data and information in those elements. Furthermore, the artefact works if appropriate data and information are available in the enterprise information systems.

Naturalistic or artificial evaluation of the design process artefact

The evaluation context of this contribution differs from that specified in Table 2. It was evaluated in an artificial context using a computer simulation. Although data and information from the two MADE manufacturing companies were shared, they were not sufficient for an evaluation. Therefore, additional simplified data and information were recreated based on the shared data and information.

Ex ante or ex post evaluation of the design process artefact

The artefact was evaluated ex post.

Criteria of the design process artefact

The evaluation used data that resembled the data of two MADE manufacturing companies; it focused on the feasibility of the artefact. The feasibility was demonstrated by executing the artefact and by enhancing EA models at the enterprise and site levels using simulated heterogeneous data. The applicability of the artefact was not evaluated, as the contribution was evaluated in only one context. The efficiency was also not evaluated because doing so would have implied a comparison between a manual method and the extended AMA4EA method, which was not undertaken.

Contribution type of the design product artefact

The design product artefact is the result of two iterations: The first iteration was conducted in the learning factory context, where the artefact was manually developed to address specific practice problems. The second iteration was created in the context of the two MADE manufacturing companies, where it was the result of the application of the design process artefact.

Generalizability level of the design product artefact

This artefact was expected to support the other artefact without being an important contribution in itself. For this reason, this contribution did not aim at any of the specific generalizability levels presented in Table 2. However, it can be argued that the instantiation of the artefact is a level 1 contribution. It was demonstrated through two iterations and examples how the artefact works.

Ex ante or ex post evaluation of the design product artefact

In both iterations, the ex post evaluations were undertaken in collaboration with the learning factory manager and using simulated data from the MADE manufacturing companies.

Criteria of the design product artefact

In the first iteration, the evaluation with the learning factory manager focused on the usefulness and feasibility of the artefact. The learning factory manager reported that the inclusion of additional data and information in the EA models provided operational support. The enhanced EA models helped him to solve errors in the production process more efficiently. The feasibility of the artefact was demonstrated by the author's creation of the EA models. This improvement does not take into consideration other artefacts that may also contribute to the enhancement of EA models.

In the second iteration, the evaluation was based on recreated data presented by one MADE manufacturing company. The feasibility of the artefact was demonstrated by the enhancement of EA models at the enterprise and site levels using heterogeneous data. The applicability of this artefact was demonstrated by enhancing EA models both at the learning factory and with simulated data from MADE manufacturing companies.

Discussion

The previously mentioned limitations of the naturalistic context, the involvement of only the learning factory manager, and ex ante evaluations for the previous contribution also apply to the artefact included in this contribution. Therefore, it will not be repeated in this section. The only addition to the previous discussion is related to the use of simulated data. This was necessary because the MADE manufacturing companies chose not to send extracts from their production event logs. These logs were only shown through the business analytics platform. The reason for this is because these event logs were considered too confidential to be distributed.

This concludes the discussion of the evaluation of the research contributions. The limitations of these research contributions are discussed in a Section 8.4. Furthermore, Section 8.5 will present the future research that could be undertaken to address these limitations.

8.2. SIGNIFICANCE FOR RESEARCH

As summarized in Table 12, the research in this thesis is important because it addresses several research gaps related to the development and use of EA methods in digital manufacturing. The research gaps (which are understood as unexplored or underexplored research areas) were described in Section 2.4, while the research contributions were discussed in Chapter 7. For each of this thesis' objectives, this section explains the significance of these contributions in addressing the research gaps.

Table 12. Summary of research gaps and contributions associated with each thesis objective

Research gaps	Research contributions
1. Exploring EA models as digital models for digital manufacturing a. Limited understanding of the design and evaluation of EA models as digital models for digital manufacturing	Design product artefact. The collection of EA models that instantiated RAMI4.0 were used as digital models for digital manufacturing to facilitate information dissemination.
2. Using data to create EA models for digital manufacturing a. Automated EA modelling methods cannot create EA models pertaining to the business aspect b. Automated EA modelling methods mostly do not use data from enterprise information systems to create EA models c. Data stored on enterprise information systems is not extended and abstracted using ontologies d. Automated EA modelling methods do not support managing process heterogeneity	Design process artefact. The AMA4EA method (including the extended AMA4EA) uses and extends with ontologies heterogeneous data from different enterprise information systems to create EA models pertaining to the business aspect at different levels of abstraction. Design product artefact. The collection of EA models (i.e. process models) created that relate and visualize heterogeneous processes at different abstraction levels (i.e. enterprise and site).
3. Using data to enhance EA models for digital manufacturing a. Automated EA modelling methods do not enhance EA	Design process artefact. The extended AMA4EA method uses heterogeneous data from different enterprise information systems to enhance EA models pertaining to

	models with additional data and information	the business aspect at different levels of abstraction.
b.	Automated EA modelling methods do not support managing data heterogeneity	Design product artefact. The collection of enhanced EA models developed and created provide operational support and relate and visualize heterogeneous data and information at different abstraction levels (i.e. enterprise and site).

8.2.1. EA MODELS FOR DIGITAL MANUFACTURING

As discussed in Section 2.1, the lack of research and industrial applications of EA models for digital manufacturing raised uncertainties concerning which EA models can be used as digital models for digital manufacturing. This thesis identified EA models that can be used as digital models in digital manufacturing. Seven different EA models were used to instantiate RAMI4.0. Although this research was conducted in an artificial context, this application is a first step towards using EA models in the Industry 4.0 transformation and digital manufacturing. It demonstrates what it can be achieved and identifies new research opportunities for EA discipline.

8.2.2. AUTOMATED EA MODELLING METHODS MODEL THE BUSINESS ASPECTS OF DIGITAL MANUFACTURING

The use of EA models as digital models for digital manufacturing requires efficient modelling approaches. As discussed in Section 2.2, existing automated EA modelling methods and process discovery are not adequate to address all aspects of EA models, namely business, application, and technology. The AMA4EA method was the missing piece in automated EA modelling methods. Other methods can only create EA models pertaining to the application and technology aspects. In contrast, the AMA4EA method creates EA models for the business aspect. With the addition of the AMA4EA method to automated EA modelling methods, all of the aspects of EA models can be modelled using automated EA modelling methods. Therefore, this contribution could lead to new EA modelling approaches. In the Industry 4.0 transformation, data is often referred to as the “new gold”. For this reason, it was important to explore how EA approaches can use data. The AMA4EA method demonstrated the use of enterprise information systems as data sources for the creation of EA models. This contribution also began to address the challenge of process heterogeneity: When process heterogeneity is documented in the data stored on enterprise information systems, it can be managed using EA models at different abstraction level, as demonstrated by the application of the extended AMA4EA. An additional contribution is related to the application of ontologies. To use enterprise information systems for creating EA models, data from these systems were extended using ontologies. The AMA4EA method can be used with different ontologies and therefore can be applied to use different data to model various aspects of an enterprise.

8.2.3. AUTOMATED EA MODELLING METHODS ENHANCE EA MODELS FOR DIGITAL MANUFACTURING

As discussed in Section 2.4, limited research has been conducted on the enhancement of EA models with data to provide operational support. The EA models developed in this thesis demonstrated how EA models can be enhanced to provide operational support, and the application of the extended AMA4EA method demonstrated how this can be automated. The inclusion of performance measurements and documentation in the EA models represents a starting point for developing feedback loops and addressing the silo mentality that may exist in some companies. This contribution is also a starting point for addressing the data heterogeneity problem.

8.3. IMPLICATIONS FOR PRACTITIONERS

As described in Section 1.4, the research in this thesis aimed at addressing three manufacturing challenges and fulfilling two requirements related to digital manufacturing. The silo mentality challenge was not included in the scope of this research, but the contributions of this thesis may still prove valuable in addressing it.

8.3.1. FACILITATING INFORMATION AVAILABILITY THROUGH EA MODELS FOR DIGITAL MANUFACTURING

The information availability challenge was addressed by designing and evaluating EA models to visualize elements and relationships in digital manufacturing. They supported the explanation of the learning factory as well as the collection of information. Furthermore, the AMA4EA method uses and extends the data stored on enterprise information systems, therefore making that information available to stakeholders without previous experience with such systems. These contributions facilitate access to information through EA models.

8.3.2. SUPPORTING PRODUCTION MANAGERS ADDRESSING PROCESS AND DATA HETEROGENEITY

As discussed in Section 1.2, functional units often lack an overview of their processes and data. This is related to the challenges that functional units experience in managing process and data heterogeneity. The AMA4EA method and the EA models created applying the method support the management of process and data heterogeneity. These EA models provide an overview of a process, access to instantiations of that process at different sites, and the relationships between each element in the EA models that present the overview of the process with the elements in the EA models at the site level. These EA models represent an initial step towards managing process and data heterogeneity. This contribution lays the foundations for communicating and comparing information concerning heterogeneous processes and data in an understandable way using EA models. Simultaneously, if detailed information is required to implement integrations between processes and enterprise information systems, the EA models developed with the AMA4EA method can specify the instantiation of the process at a more detailed level, as well as important information stored on an enterprise information system in the elements in EA models. The research presented in this thesis focused on the manufacturing functional unit and modelling its processes and data. Therefore, this thesis contributes towards the integration of the manufacturing functional unit with the other functional units in an enterprise.

8.3.3. PROVIDING OPERATIONAL SUPPORT WITH EA MODELS

As discussed in Section 1.2, the Industry 4.0 transformation requires functional units to be integrated. This integration is challenging because functional units need to better understand their processes and data and to share them with other units. Enterprise architecture can support the integration of functional units by sharing information about processes and resources across such units. The EA models created demonstrated their ability to support the monitoring of products, resources, and processes in the learning factory. The EA models were also helpful in the management of errors and problems.

8.3.4. A NEW APPROACH TO EA MODELLING

As discussed in Section 2.2, EA modelling is inefficient, time-consuming, and error-prone (Hauder, Matthes, and Roth 2012; Buschle et al. 2012; Hauder et al. 2013; Holm et al. 2014). This is problematic for enterprise architects, as they need to spend considerable amounts of time developing EA models. The automated EA modelling method, and, in particular, AMA4EA contribute towards transforming EA modelling and making it more efficient. These automated EA modelling methods may lead to the use of EA models as digital models.

8.4. LIMITATIONS

The research presented in this thesis was subject to three main limitations: first, the limited understanding of enterprises' problems related to digital manufacturing; second, the focus on one reference architecture model and the modelling of EA models related to the business aspect; and, third, the limited understanding of how practitioners use EA models in manufacturing.

8.4.1. DIGITAL MANUFACTURING

As discussed in Section 3.2, gaining access to manufacturing companies was very difficult. This resulted in the choice to demonstrate the contributions in the learning factory, with the demonstration subsequently being used to involve and gain access to manufacturing companies. The presentation of the demonstration developed in the learning factory to manufacturing companies may have been influenced the collection of practitioners' problems. Therefore, when interviewing managers in companies only a limited amount of time was devoted to the identification of problems not related to the demonstration in the learning factory. A significant amount of time was spent on the identifying the benefits and approach related to the application of the demonstration in a manufacturing company. This may have impacted the author's understanding of manufacturing companies' existing solutions and problems. Furthermore, it was also difficult to gain access to the manufacturing companies to evaluate the further developments of the artefacts intended to address their problems. Finally, the selection of manufacturing companies was not impartial and required pre-existing connections with employees working in each company. For this reason, it was possible to closely collaborate with only a limited number of manufacturing companies. This also affected the author's understanding of the problems faced in the manufacturing industry. For example, all the MADE manufacturing companies involved in this research only operated one ERP system each. In the last months of the research conducted for this dissertation, the author realized that other companies in the manufacturing industry operate with multiple ERP systems. However, this limitation is to be expected in a study of this kind, in which the author sought to understand problems by focusing on only a limited number of industrial collaborations.

8.4.2. EA MODELS

Three main limitations related to EA models were identified. Although Section 2.1.2 presented three reference architecture models relevant for digital manufacturing, this thesis focused only on the instantiation of RAMI4.0. Therefore, the identification of the EA models that can serve as models for digital manufacturing was based on RAMI4.0. However, this limitation is unlikely to have had a major effect due to the fact that these reference architecture models share a significant number of elements. For example, as noted in an article by a subject-matter expert, the architectural layers in RAMI4.0 can be associated with aspects of IIRA.[17] In addition, RAMI4.0 and GERAM share elements, as they are both related to the ISA 95 standard (International Electrotechnical Commission 2013).

Another limitation is the fact that the AMA4EA method was only applied to develop an EA model related to the business aspect. Given that the development of the AMA4EA method was completed in May 2019, there was no time to demonstrate the use of the method for creating EA models pertaining to the application and technology aspects. For the same reason, the demonstration of the method focused only on process models. Other EA models related to the business aspect could also be developed, but they would require the identification of new data and new ontologies, as well as the

[17] https://coe.qualiware.com/reference-architectures-for-industry-4-0/

preparation of the AMA4EA environment and QualiWare ApS EA repository for these ontologies.

The third limitation concerns the use of the term EA models in this thesis. When referring to EA models for digital manufacturing, out of the many types of existing EA models, only a few were considered (i.e. strategic, process, data, application, infrastructure and communication, product, and equipment models).

8.4.3. EA MODELLING

A limitation related to EA modelling is the fact it was not possible to interview enterprise architects until the author began collaborating with the Swedish manufacturing company. Therefore, the author's understanding of EA modelling was mostly based on his previous work experience and meetings with employees at QualiWare ApS. From these meetings and the discussions with the enterprise architect from the Swedish company, it emerged that EA models are not used to model manufacturing. However, no further investigations into the reasons why this is the case were possible. Having stated this, however, the research community, as well as several EA practitioners, validated the usefulness of the EA models and the AMA4EA method.

8.5. RECOMMENDATIONS FOR FUTURE RESEARCH

The contributions presented in this thesis may represent starting points for future research. Three main future research directions can be identified.

8.5.1. NEW EA MODEL MAINTENANCE METHODS FOR MANAGING EA MODELS

Automated EA modelling methods address the problem of inefficient, time-consuming, and error-prone EA modelling methods. However, the significant increase in number of EA models requires new research intended to support the management of these models. Keeping EA models aligned with the data stored on enterprise information systems is expected to be a major challenge. Research on this topic has begun (Farwick et al. 2012; Hansen and Hacks 2017), but more is required.

8.5.2. ALIGN DATA ACROSS SYSTEMS

Automated EA modelling methods could be extended to create EA models from data from multiple systems with the goal of facilitating the alignment of data across systems. It would be interesting to use ERP and product lifecycle management systems as data sources in the AMA4EA method to investigate how the data concerning production processes stored on these systems differs, to understand these differences, and to find a solution with which to manage such differences. This future research direction closely relates to the process and data heterogeneity problems addressed in this thesis.

8.5.3. DATA SOURCES

Research focused on the application of the AMA4EA method to support other functional units would require the use of other systems (e.g. product lifecycle management, customer relationship management, or IoT platforms). Enterprise resource planning systems and MESs were used as main data sources for AMA4EA, but these systems are related mainly to the manufacturing functional unit. In a typical enterprise, there are several other enterprise information systems (e.g. product lifecycle management and customer relationship management systems). These systems could be used for the creation of EA models related, for example, to product architecture and customer bases. In addition, different types of sources of event logs could be used to enhance EA models (e.g. IoT platforms with data from IoT devices and smart products).

8.6. REFLECTION

Following the evaluation and positioning of the research contributions, it is important to reflect on the research conducted for this thesis. Although many points could be discussed, the three main points of reflection are presented below.

The first point focuses on the alignment of this thesis' objectives with the needs of the empirical context. As discussed in Section 3.2, the stakeholders in the empirical context of the research in this thesis expected the development of solutions intended to address their problems. Therefore, this thesis focused on design and evaluation research. However, the objectives could have been separated from the needs of the stakeholders in the empirical context. These needs could have been pursued outside of the work conducted for this dissertation. This would have opened the possibility of engaging in other research forms (e.g. case study research on the use of digital models for smart products or investigating whether and how enterprise architects model manufacturing processes). The purpose of such research would have been more to explain reality rather than to design artefacts intended to solve problems.

The second point of reflection relates to the level of the contributions presented in this thesis. The use of EA models for digital manufacturing is a very specific research contribution that could have been abstracted and made more generalizable in a number of ways, such as by undertaking a more detailed analysis of QualiWare ApS's EA models and RAMI4.0 layers, identifying the important elements in these models and layers, and relating these elements to more general concepts used in EA research and by practitioners. This would have significantly improved the generalizability of the first research contribution to the second level.

The third point of reflection concerns the evaluation of the artefacts developed in this thesis. The difficulty in interacting with the manufacturing companies limited the evaluation of the artefacts. As shown in Figure 10, the most significant collaborations occurred during the second half of the research conducted for this dissertation. The author's understanding of manufacturing and associated problems in the first half of the research period may have been thus fragmented. Based on this understanding, solutions to the problems identified were developed. This led to several interactions with a handful of manufacturing companies (e.g. Enterprise A and C). However, the level of these interactions remained superficial throughout the research period. To address these problems, greater efforts could have been devoted towards entering into collaborations with fewer manufacturing companies and working with them throughout the course of this research. However, this could have been achieved by making separate contributions to QualiWare ApS and the manufacturing companies.

CHAPTER 9. CONCLUSION

This thesis set out to explore the contribution of EA discipline to the Industry 4.0 transformation and enterprises' transitions to digital manufacturing. Its purpose was to both explore the development of EA models for digital manufacturing as well as to enhance EA models to provide the operational support required to enhance manufacturing products and processes. Chapter 1 explained the transition to digital manufacturing and its main challenges and requirements.

The three main challenges, which are information availability, process and data heterogeneity and silo mentality are widely experienced by manufacturing companies. Besides these challenges, the transition to digital manufacturing requires digital models, feedback loops, and integration. To address these challenges and fulfil these requirements, the research in this thesis was structured around three objectives: (1) exploring the development and use of EA models as digital models for digital manufacturing, (2) using data to create EA models for digital manufacturing, and (3) using data to enhance EA models for digital manufacturing. The main concepts and research gaps associated with each of these objectives were presented in Chapter 2. Chapter 3 outlined the research design and the choices made and goals set.

Based on the six articles written during the course of the author’s PhD studies, Chapters 4, 5, and 6 summarized the research contributions made by each article towards this thesis' objectives. The main research contributions of Chapter 4 were the identification and use of EA models for digital manufacturing. Furthermore, Chapter 4 explained how EA models can be used to facilitate information dissemination. The main research contributions of Chapter 5 were a new automated EA modelling method for creating EA models related to the business aspect, the use of ontologies in this method to extend data obtained from enterprise information systems, and the creation of EA models for managing process heterogeneity. The main research contributions of Chapter 6 were a method for enhancing EA models related to the business aspect with additional data and information to provide operational support, as well as to support the management of data heterogeneity through EA models. These research contributions were synthesized in Chapter 7 and evaluated in Chapter 8.

The several implications of the research contributions were discussed in Chapter 8.

The first implication was the improved information availability resulting from the use of EA models to communicate and collect information about digital manufacturing. The second was the ability of EA models to provide overviews of and access to the details of functional units' processes, even in cases of process and data heterogeneity. Finally, the third implication was the ability of EA models to provide operational support to help managing error and problems.

As discussed in Chapter 8, the research conducted for this thesis was subject to three main limitations. First, before access to manufacturing companies could be gained, the author first had to develop and demonstrate solutions in the learning factory. Therefore, the author's understanding of enterprises' problems was influenced by solutions related to digital manufacturing. Second, the research focused on one reference architecture model and the modelling of EA models related to the business aspect. However, the reference architecture models for digital manufacturing have many elements in common. In addition, the EA models created with the AMA4EA method focused on the business aspect, as other automated EA models fail to address this aspect. The application of the AMA4EA method for modelling the other aspects could be undertaken in the future. Third, the interaction with an enterprise architect in a manufacturing company occurred relatively late during the course of this research. It was thus not possible to investigate how EA models are used to model manufacturing. However, the research community and other practitioners validated the usefulness of the EA models and AMA4EA.

As a continuation of the research presented in this thesis, three future research directions were presented. First, the creation of EA models based on data could significantly increase the number of EA models that need to be managed. Future research into ensuring that EA models remain aligned with the data stored on enterprise information systems will be required. Second, it will be necessary to explore how data on different systems that relate to the same concept can be aligned. For instance, production processes are usually stored on at least three systems: product lifecycle management, ERP, and MES. Enterprise architecture models could be applied to manage process heterogeneity among these systems and facilitate communication concerning production processes across functional units. Third, the use of the method to create models of functional units, other than manufacturing, using the data from their enterprise information systems should be investigated.

This thesis demonstrated the viability of using EA models for digital manufacturing and presented an automated EA modelling method with which to create and enhance EA models based on data. This body of knowledge will likely prove beneficial to researchers and practitioners involved in the Industry 4.0 transformation and the transition to digital manufacturing. This thesis also provided concrete tools and demonstrations that can be replicated in both research and industrial contexts. Further application of these EA models and method could be investigated to evaluate and improve their contributions to the feedback loops and integration required by the Industry 4.0 transformation.

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APPENDIX A

As presented in Section 3.2, below an anonymized example of field notes recorded on the same day of the interview.

Challenges of [name] team at [company name]

Participants: [name interviewee], Marco
Place: [company name]
Date: […]

Introduction [contextual information like organizational structure, goals and activities of the team].

Challenges

This section is structured as follows. There are 5 challenges and for each of them there is a list of problems. Below each problem, there is the quote from the interview or the minutes during the interview when that problem was mentioned. Each problem has comments by Marco, Charles and John.

1. **Challenge in New Product Development for System of Systems**
   Product development has shifted from being siloed and focused on a single system, to being collaborative across departments and focused on System of Systems. This shift made necessary to have an end-to-end view of the System of Systems.

   Quote [00:07:05] – Challenges in new product development and the creation of the [name] unit.

   "So the point here is that we have people from this department up here and people from this department down here [name]. Before the way we have been doing products was somehow much easier […]. And these guys here [name] have been more or less being contained. Now you have to talk to a lot of different things, even taking in third party components. And why is this important? Because if you want to offer an […] you need to have an end-to-end view on it. This is why […] was formed […] years ago, […] we have end to end responsibility of […] products."

   Marco: This could be used as motivation for the research.

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