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POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

A framework to support Industry 4.0 initiatives in manufacturing companies

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
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Cette thèse intitulée :

A framework to support Industry 4.0 initiatives in manufacturing companies

présentée par **William DE PAULA FERREIRA**
en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

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DEDICATION

To my wife Marinalva, my son William Lott, my parents Maria and Gilmar,
and to the memory of my grandmother Maria do Carmo.

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RÉSUMÉ

L'industrie 4.0 est une stratégie majeure visant à promouvoir l'innovation et à améliorer la compétitivité du secteur manufacturier dans une économie mondiale de plus en plus numérisée. Cette stratégie est souvent associée à des principes et des technologies qui ont des implications sur la création de valeur, les modèles d'affaires, l'organisation du travail et la performance. L'industrie 4.0 a été principalement déclenchée par la nécessité de raccourcir les cycles d'innovation, l'individualisation de la demande et l'efficacité des ressources, et est stimulée par des avancées et l'accès aux technologies de l'information, de la communication et de l'automatisation. Malgré sa pertinence, il y existe toujours un manque de compréhension de ce concept, de ses méthodes et des outils qui aident les entreprises à faire la transition numérique. Ce manque est particulièrement présent chez les petites et moyennes entreprises (PME), où l'industrie 4.0 est encore sous-exploitée. Cette thèse de doctorat, qui résulte d'une recherche collaborative avec un centre collégial de transfert de technologie canadien, vise à améliorer la compréhension du concept de l'Industrie 4.0 et à développer des artéfacts de modélisation pour soutenir les initiatives de l'Industrie 4.0 dans les entreprises manufacturières. Il s'agit d'une recherche ayant pour but de contribuer au développement des connaissances scientifiques ainsi qu'à la pratique, basée sur la méthodologie du «Design Science». Étant multidisciplinaire, cette recherche est à l'intersection de trois domaines de recherche : l'industrie 4.0, la modélisation et simulation de systèmes, et le «Lean». Ce faisant, elle vise à apporter trois contributions principales. La première contribution se concentre sur le développement d'une revue de l'état de l'art visant à analyser et à caractériser l'industrie 4.0, plus particulièrement du point de vue de la simulation, présentée par certains auteurs comme un domaine d'action prioritaire pour soutenir le développement de l'industrie 4.0. La deuxième contribution consiste à proposer un cadre pour l'identification et l'analyse des scénarios d'application de l'industrie 4.0. Ce cadre prend en compte le modèle d'architecture de référence pour l'industrie 4.0 et une approche de modélisation hybride, combinant la modélisation à évènements discrets et à base d'agents. En ce qui a trait à la troisième contribution, l'accent a été mis sur le développement d'un cadre de modélisation pour soutenir des initiatives de l'Industrie 4.0 dans les entreprises manufacturières (principalement des PME), étendant la traditionnelle cartographie des chaînes de valeur au contexte de l'industrie 4.0. Ce cadre a été testé et évalué à travers une étude de cas dans une PME canadienne faisant une transition vers l'industrie 4.0. En somme, cette thèse contribue à mieux comprendre les construits de l'Industrie 4.0, ainsi qu'à identifier, modéliser, simuler et analyser des scénarios d'application de l'Industrie 4.0 pour soutenir ses initiatives dans les PME manufacturières.

ABSTRACT

Industry 4.0 is a central strategy to innovate and increase the manufacturing sector's competitiveness in an increasingly digital global economy. It is associated with principles and technologies, with implications for value creation, business models, work organization, and performance. Industry 4.0 was mainly triggered by the need to shorten development and innovation cycles, individualization of demand, resource efficiency, and is driven by significant advancements and access to information, communication, and automation technologies. Despite its increasing relevance, there is still a lack of understanding of the Industry 4.0 concept, and methods and tools to support companies' transition towards Industry 4.0 are still scarce, especially for small and medium-sized enterprises (SMEs), where it is still underexploited. This Ph.D. thesis, which results from a collaborative research with a Canadian College Centre for Technology Transfer (CCTT), aims to enhance the understanding of Industry 4.0 constructs and develop modeling artifacts to support Industry 4.0 initiatives in manufacturing companies. It consists of knowledge and practice-enhancing research based on the design science paradigm. It is multidisciplinary, framed at the intersection of Industry 4.0, Modeling & Simulation, and Lean Manufacturing fields, providing three main contributions. The first contribution is to develop a state-of-the-art review to analyze and characterize Industry 4.0 key constructs and the development of simulation-based research in Industry 4.0, featured as a priority area for action to support the development of Industry 4.0. The second contribution consists of proposing a framework for identifying and analyzing Industry 4.0 scenarios for application, which considers the reference architecture model for Industry 4.0 (RAMI4.0) and a hybrid modeling approach that combines discrete-event agent-based modeling and simulation. In the third contribution, the focus is on developing a new modeling framework to support the development of Industry 4.0 initiatives in manufacturing companies (mainly SMEs) by extending the Lean Value Stream Mapping (VSM) to the context of Industry 4.0, which was evaluated through a proof-of-concept case developed in a Canadian SME from the furniture and related product manufacturing sector investing in Industry 4.0. Overall, this Ph.D. thesis contributes to better understanding Industry 4.0 constructs, identifying, modeling, simulating, and analyzing Industry 4.0 application scenarios and examples to support Industry 4.0 initiatives in manufacturing companies.

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LIST OF SYMBOLS AND ACRONYMS

ABMS	Agent-Based Modeling and Simulation
ADACOR	ADAptive holonic COntrol aRchitecture
BPMN	Business Process Model and Notation
CCTT	College Centre for Technology Transfer
CPS	Cyber-Physical Systems
DES	Discrete-Event Simulation
HS	Hybrid Simulation
IoT	Internet of Things
I4.0	Industry 4.0
LM	Lean Manufacturing
MAS	Multi-Agent Systems
M&S	Modeling and Simulation
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturer
OR	Operational Research
PROSA	Product Resource Order Staff Architecture
RAMI4.0	Reference Architecture Model for Industry 4.0
SMEs	Small and Medium-sized Enterprise
UML	Unified Modeling Language
VSM	Value Stream Mapping
WIP	Work In Process

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CHAPTER 1 INTRODUCTION

"It began with a dream"
– Dr. Gladys Mae West

This chapter presents the general introduction of the Ph.D. thesis, divided into seven sections. The first section describes the context of the research, and the second section presents the problem statement. The third and fourth sections determine the research questions and objectives based on the problem statement, respectively. The fifth section introduces the main contributions of this thesis, and the sixth section delineates its scope. Lastly, the seventh section outlines the organization of the thesis.

1.1 Context

The early 21st century is characterized by an ongoing manufacturing paradigm shift due to significant changes in supply-demand relationships, and advancements and access to new information, communication, and automation technologies, such as the internet of things (IoT), cyber-physical systems (CPS), cloud computing, big data analytics, modeling and simulation, and collaborative robots (Kagermann et al., 2013; Liao et al., 2017; Hofmann and Ruesch, 2017; Yin et al., 2018; Müller et al., 2018). It is also characterized by the emergence of new business models and strategies, such as mass customization (or Lot Size One), which emphasizes differentiation as a primary competitive advantage and flexibility and agility as primary performance measures (Arnold et al., 2016; Müller et al., 2018; Weking et al., 2020).

This trend (or paradigm shift) has been referred to in the literature as Industry 4.0, i.e., the Fourth Industrial Revolution. This term emerged at the Hannover Fair in 2011 as part of Germany's long-term strategy to increase the competitiveness of its manufacturing sector (Liao et al., 2017). It refers to "a collective term for technologies and concepts of value chain organization" (Hermann et al., 2015, p. 11), having implications on product lifecycle, business models, work organization, resource efficiency, and operational performance (Kagermann et al., 2013; Schwab, 2017). According to Kagermann et al. (2013), one of the first studies that described the vision, potentials, research requirements, priority areas for actions, and recommendations for implementing Industry 4.0, it "will lead to the emergence of dynamic, real-time optimized, self-organizing value chains that can be optimized based on criteria such as cost, availability, and resource consumption" (Kagermann et al., 2013, p.20).

After its emergence in 2011 and discussion at the 2016 World Economic Forum, Industry 4.0 gained worldwide attention from researchers, industries, and governments (Kagermann et al., 2013; Liao et al., 2017; Schwab, 2017; Xu et al., 2018) and has become a hot research topic (see Fig. 1.1). It has been considered one of the main strategies to promote innovation and increase the manufacturing sector's competitiveness in a growing digital global economy over the following years (Schwab, 2017; Müller et al., 2018; Deloitte, 2018; CMC, 2021). A global survey on Industry 4.0 (with more than 2,000 participants) suggested that around 5% of companies annual revenue will be invested in digitalization projects (PwC, 2016). Another global survey on digital transformation (with more than 350 executives) also suggests that investing in Industry 4.0 is an organizational imperative (Deloitte, 2018).

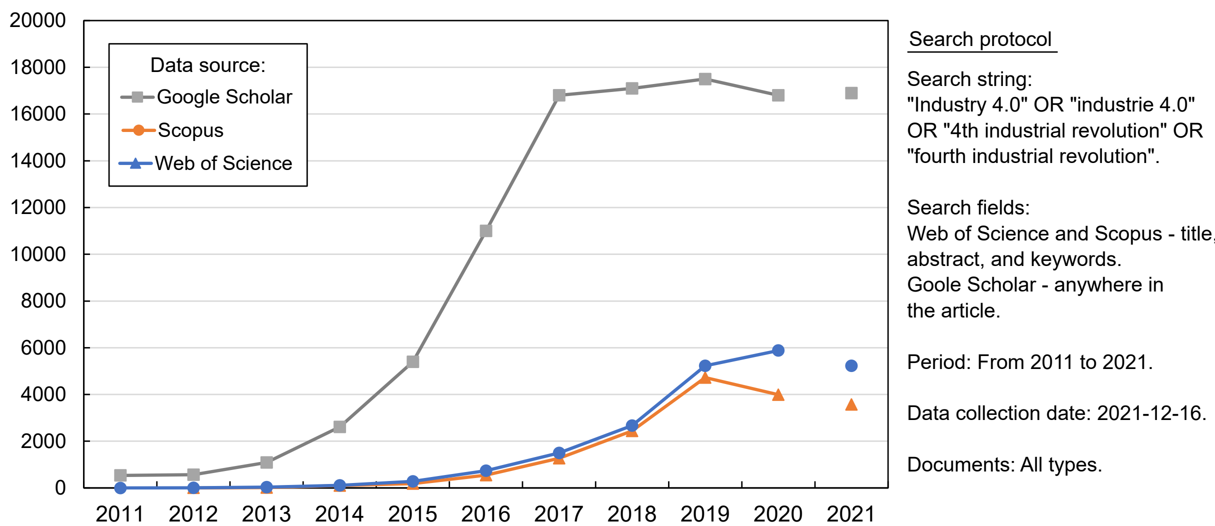

Figure 1.1 Evolution of publications on Industry 4.0 over the years

1.2 Problem statement

Despite its increasing relevance, there is still a lack of shared understanding of Industry 4.0, and it is not yet well-established in practice (Liao et al., 2017; Hofmann and Ruesch, 2017; Moeuf et al., 2018; Müller et al., 2018; Masood and Sonntag, 2020; Stentoft et al., 2020; Culot et al., 2020). Moreover, there is still a lack of methods and tools to help companies move towards Industry 4.0, especially for small and medium-sized enterprises (SMEs), where Industry 4.0 is still under-exploited (Hofmann and Ruesch, 2017; Moeuf et al., 2018; Müller et al., 2018; Masood and Sonntag, 2020; Stentoft et al., 2020). At the same time, SMEs are increasingly interested in implementing Industry 4.0, whether driven by internal motivation or by pressure from customers and/or large companies, such as from Original Equipment

Manufacturers (OEM) fearing being forced out of the market if they do not comply with their requirements (Müller et al., 2018; Masood and Sonntag, 2020).

Implementing Industry 4.0 initiatives in a company (especially in SMEs), in general, is a complex, challenging, and resource-demanding process, from the financial and organizational perspectives, involving significant changes in infrastructure, processes, operations, work organization, skill requirements, and business models (Lichtblau et al., 2015; Veile et al., 2019; Müller et al., 2018; Abar et al., 2017; Agostini and Nosella, 2020; Weking et al., 2020). That is why Industry 4.0 is an intimidating concept for many SMEs (Müller et al., 2018). Moreover, "there is no one-size-fits-all solution for companies" seeking to implement Industry 4.0 (Lichtblau et al., 2015, p. 56). There is a need to help SMEs to identify areas of their business that could be positively impacted by the Industry 4.0 principle and technologies and how they should be implemented to overcome perceived challenges faced by those companies (e.g., lack of infrastructure, expertise, financial resources) to accelerate Industry 4.0 implementation (Lichtblau et al., 2015; Moeuf et al., 2018; Fitzgibbon, 2019; Da Silva et al., 2020; Stentoft et al., 2020; Ghadge et al., 2020).

Many of these issues can be addressed through computer-based modeling and simulation technologies that offer enormous potential to support the implementation of Industry 4.0 (Kagermann et al., 2013). They can be used for developing planning and explanatory models to optimize the design and operations of complex production systems and support decision-making, helping companies evaluate the risks, costs, implementation barriers, impacts on operational performance, and roadmap toward Industry 4.0 (Kagermann et al., 2013). Nevertheless, the advancement of Industry 4.0 poses challenges to the field of modeling and simulation, given the growing complexity of systems to be modeled (Kagermann et al., 2013). Moreover, mainly in SMEs, "it is still not standard practice to use model-based simulations in order to configure and optimize manufacturing processes" (Kagermann et al., 2013).

Lean Manufacturing, a strategy widely used to increase companies' operational performance (Bhamu and Sangwan, 2014), can also help address the issues mentioned above through its principles and practices. Indeed, it is considered by some authors as a prerequisite for implementing Industry 4.0 (Buer et al., 2018; Ciano et al., 2021). Moreover, many researchers suggest that Lean Manufacturing has enabling effects on Industry 4.0 and vice versa (Sanders et al., 2016; Buer et al., 2018, 2021a; Tortorella and Fettermann, 2018; Tortorella et al., 2019; Matteo et al., 2019; Shahin et al., 2020a; Rosin et al., 2020; Tortorella et al., 2021; Ciano et al., 2021). However, the literature falls short on how Lean principles and practices can support Industry 4.0 (Buer et al., 2018; Ciano et al., 2021).

1.3 Research questions

Based on the problem statement above, this study seeks to answer the following questions[1]:

1. How can we operationalize the Industry 4.0 concept into application scenarios?
2. How can we model and simulate Industry 4.0 application scenarios?
3. How can we support Industry 4.0 initiatives in manufacturing SMEs?

1.4 Objectives

Based on the problem statement and research questions above, the general objective of this Ph.D. thesis is to enhance the understanding of Industry 4.0 constructs and develop artifacts[2] to support Industry 4.0 initiatives in manufacturing companies, both timely and aligned with current academic and industrial needs and interests.

The specific objectives of this thesis, drawn from the general objective above are as follows:

1. To identify the main constructs of Industry 4.0 and characterize the current state of the art of simulation in Industry 4.0;
2. To develop a framework[3] for identifying and analyzing Industry 4.0 scenarios;
3. To develop a framework to support Industry 4.0 initiatives in manufacturing SMEs.

To achieve the objectives of this thesis, a knowledge and practice-enhancing research framed at the intersection of three research fields (i.e., Industry 4.0, Modeling & Simulation, and Lean Manufacturing), multidisciplinary in nature, was conducted based on the Design Science Research (DSR) method that addresses research through the development and evaluation of new artifacts (Hevner et al., 2004; Gregor and Hevner, 2013).

[1]These questions follows the guidelines provided by Thuan et al. (2019) on how to formulate suitable design science research questions.

[2]The term artifact is "broadly defined as constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems" (Hevner et al., 2004, p. 77).

[3]The term framework refers to a set of modeling principles, methods, or tools relevant to an application domain, as defined by Vernadat (1996).

1.5 Contributions

This Ph.D. thesis by articles provides three main contributions, described as follows.

The first contribution focuses on developing a state-of-the-art review to characterize Industry 4.0 principles and analyze the development of simulation-based research in Industry 4.0, summarized into an analytical framework. It mainly addresses one of the eight priority areas for action (i.e., managing complex systems) to support the development of Industry 4.0 pointed out by Kagermann et al. (2013). According to them, modeling and simulation is a key enabling technology for managing complex systems and "one major challenge for Industry 4.0 will therefore be to raise awareness of models' potential among the wider engineering community and equip engineers with methods and tools for using appropriate models to depict real-world systems in the virtual world" (Kagermann et al., 2013, p. 43). Despite the many advances that have been made in this field, at the time this research was conducted, studies that investigated the development of simulation-based research in Industry 4.0 were still scarce, and a state-of-the-art review on simulation in Industry 4.0 was missing.

The second contribution consists of proposing a framework for identifying and analyzing Industry 4.0 scenarios for supporting Industry 4.0 roadmap development, which involves defining a sequence of measures for an organization to achieve higher Industry 4.0 maturity levels. It extends the analytical framework presented in the previous contribution and considers the reference architecture model for Industry 4.0 (RAMI4.0) and a hybrid simulation (HS) approach that combines discrete-event simulation (DES) and agent-based modeling and simulation (ABMS). This research was developed in collaboration with a Canadian college centre for technology transfer (CCTT). It addressed the lack of practice-enhancing research – encompassing the development and assessment of use cases and knowledge-enhancing research – concerning implementation strategies and roadmaps, indicated by many scholars (Schneider, 2018; Hofmann and Ruesch, 2017; Masood and Sonntag, 2020).

The third contribution centers on integrating Lean Value Stream Mapping (VSM) with HS (DES+ABMS) to support Industry 4.0 initiatives in manufacturing companies, complementing the previous contribution. An HS-VSM framework is proposed and evaluated through a case developed in a Canadian SME from the furniture and related product manufacturing sector. It addresses the gaps in the literature on how Lean principles and practices can support Industry 4.0 (Buer et al., 2018) and the "lack of frameworks for the integration of Industry 4.0 techniques, such as simulation, and Lean" Uriarte et al. (2020, p. 95).

Overall, this thesis contributes to better understanding Industry 4.0 constructs, identifying, modeling, simulating, and analyzing Industry 4.0 scenarios for application in companies.

1.6 Scope

The scope of this research was limited as follows. First, the sector of application was delimited to manufacturing companies, following the initial scope of Industry 4.0 (Kagermann et al., 2013), with a particular focus on SMEs. Second, in terms of Industry 4.0 technologies, this study focused on modeling and simulation, mainly DES and ABMS. Third, the research focused on Lean VSM, which is a visual mapping technique widely used by the Lean community and widespread practice in industry (Shou et al., 2017; Lugert et al., 2018; Uriarte et al., 2020). In addition, it is important to note that Industry 4.0 is considered a new social-technical system involving multiple dimensions of technological, social, and economic aspects (Schwab, 2017; Yin et al., 2018). This study focused on the technology aspects/dimension of Industry 4.0 used for process innovation to improve companies' operational performance. Other aspects/dimensions such as human factors and human modeling in Industry 4.0 systems were left out of the scope of this research.

1.7 Organization of the thesis

This thesis is structured by articles and is organized as follows. Chapter 2 provides a review of relevant previous work related to the research topics that frame this thesis. Chapter 3 describes the research methodology. Chapters 4, 5, and 6 introduce the three contributing articles, addressing the research gaps and objectives mentioned above respectively as follows:

> Chapter 4: **de Paula Ferreira, W.**, Armellini, F., and De Santa-Eulalia, L. A. (2020). Simulation in industry 4.0: A state-of-the-art review. Computers & Industrial Engineering, 149:106868.
>
> Chapter 5: **de Paula Ferreira, W.**, Armellini, F., De Santa-Eulalia, L. A., and Thomasset-Laperrière, V. (2021). A framework for identifying and analysing Industry 4.0 scenarios. Submitted to Computers & Industrial Engineering.
>
> Chapter 6: **de Paula Ferreira, W.**, Armellini, F., De Santa-Eulalia, L. A., and Thomasset-Laperrière, V. (2021). Extending the lean value stream mapping to the context of Industry 4.0: an agent-based technology approach. Submitted to the Journal of Manufacturing Systems.

Chapter 7 presents a general discussion of the thesis, linking and showing the complementarity of these three contributing articles. Lastly, conclusions, limitations, and opportunities for future research are outlined in Chapter 8.

CHAPTER 2 CRITICAL LITERATURE REVIEW

"The past, like the future, is indefinite and exists only as a spectrum of possibilities"
– Stephen Hawking

This research is multidisciplinary in nature, framed at the intersection of three research fields: Industry 4.0 (I4.0), Modeling and Simulation (M&S), and Lean Manufacturing (LM), which is featured as a hot emerging research area. The majority of the studies analyzed (cited) in this Ph.D. thesis were published in the last five years (see Fig. 2.1), bringing new and important insights for those interested in this research area. In order to provide a background for the subsequent chapters, considered to achieve the earlier mentioned objective, and describe how these fields interrelate, the review of the literature first focuses on the concept and implementation strategies of I4.0, M&S, and LM. Then, it looks at the potential contributions of M&S and LM to support I4.0 and highlights the research gaps addressed in this thesis.

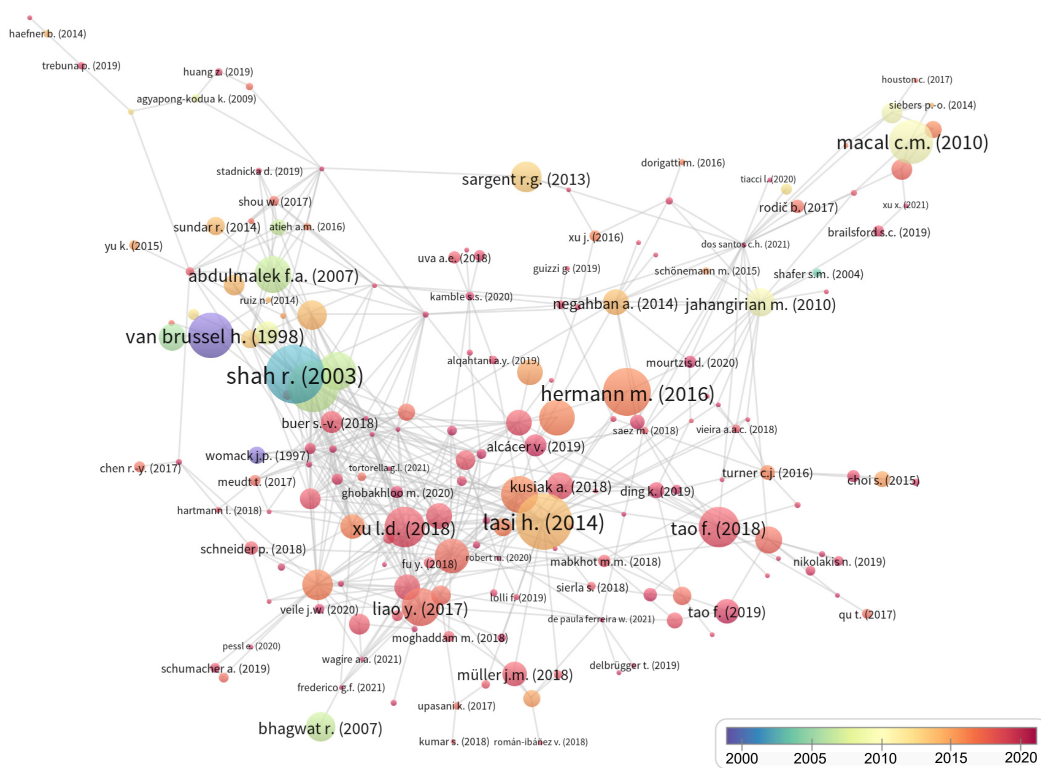

Figure 2.1 Citation bibliometric network

Legend: Each node represents a publication, the node's size represents the number of citations, the node's color represents the year of publication, and the edges represent direct citation relations between nodes.

2.1 Industry 4.0

The foundation of Industry 4.0 (I4.0) is based on the internet of things (IoT) and cyber-physical systems (CPS), as underlined in Kagermann et al. (2013). However, the number of back and front-end I4.0 enabling technologies is extensive and continues to evolve, becoming more and more mature and accessible to companies (Ghobakhloo, 2018; Alcácer and Cruz-Machado, 2019). Most of them have a long development history, dating back several years before the emergence of I4.0. The novelty of I4.0 lies mainly in its feasibility due to the increasing number of commercially available technologies, the growth of companies' digital capabilities, and intra and cross-company integration through complex value chain networks (Li et al., 2017b; Schneider, 2018). According to Professor Klaus Schwab (2017), founder and executive chairman of the World Economic Forum, it is the integration of these technologies and their synergy across the physical, digital and biological domains that characterizes I4.0. Concerning its requirements (or design principles), Hermann et al. (2016) identified four essential characteristics of I4.0 to guide companies to develop appropriate solutions: interconnection, decentralized decisions, information transparency, and technical assistance.

Concerning the implementation of I4.0, there is enough support in the literature suggesting that one of the first steps a company needs to take to start its transition towards I4.0 is to assess its degree of readiness/maturity related to I4.0 (Lichtblau et al., 2015; Wagire et al., 2020). To do so, there are several models available in the literature that can be adopted (Mittal et al., 2018; Wagire et al., 2020; Schumacher et al., 2016; Schuh et al., 2017; Lichtblau et al., 2015). Overall, they are composed of a set of maturity dimensions (e.g., strategy, smart factory, smart operations, smart products, data-driven services, employees) with different maturity items related to I4.0 principles and technologies and classified in different maturity score levels (Wagire et al., 2020). Its use enables organizations not just to assess their capabilities and transformation status but also to perform a maturity gap analysis, in which the as-it-is state and target-state for each maturity item are analyzed and defined respectively, to prioritize areas for developing I4.0 initiatives (Schumacher et al., 2019) as well as perform competitive benchmarking (Lichtblau et al., 2015).

After that, a company needs to develop a proper I4.0 roadmap, establishing goals and steps to reach the desired I4.0 maturity levels based on concrete projects to facilitate its progression towards I4.0 (Peukert et al., 2020). There are also several I4.0 roadmap models available in the literature that can be used (Beaudoin et al., 2016; Pessl et al., 2017; Hermann et al., 2016; Ghobakhloo, 2018; Schumacher et al., 2019; Peukert et al., 2020). They are composed of different phases (e.g., analysis, objective, implementation), involve different project management tools (e.g., business model canvas, balanced scorecard, cost-benefit analysis), and are usually developed with a multidisciplinary team (Peukert et al., 2020; Pessl et al., 2017).

A critical activity in developing an I4.0 roadmap is defining I4.0 scenarios and examples for application in companies (Beaudoin et al., 2016; Anderl et al., 2016), especially because I4.0 is neither well understood (there is no consensus definition of I4.0) nor established in practice (Moeuf et al., 2018; Müller et al., 2018). An I4.0 scenario encompasses one or more design principles and technologies of I4.0 (Hermann et al., 2015, 2016), serving as a conceptual model for developing practical applications to realize the potential of I4.0 (e.g., improve decision-making, product quality, increase productivity, energy efficiency). There are different existing approaches to identify I4.0 scenarios in the literature, which focus mainly on Business Model Innovation - BMI (Anderl et al., 2016; Weking et al., 2020).

I4.0 is a multifaceted and multidisciplinary topic. To consolidate its main aspects in a standard model, support consensus (e.g., common perspective, shared understanding, identify industrial standards, locate use cases), and facilitate I4.0 developments, the Reference Architecture Model for Industry 4.0 (RAMI4.0) was introduced (Adolphs et al., 2015) and gained broad acceptance, forwarded for standardization initially as DIN SPEC 9134 (2016) and then as IEC PAS 63088 (2017). It consists of a three-dimensional multi-level model used to logically describe an asset or a combination of multiple assets, which refer to objects of value for an organization, whether tangible or not (i.e., physical or virtual objects) such as a whole manufacturing facility or part of it (DIN SPEC 9134, 2016).

As described in DIN SPEC 9134 (2016), the RAMI4.0 is composed of three axis: (1) layers (i.e., asset, integration, communication, information, functional, business) - used to represent the relevant information of an asset; (2) life cycle & value stream - used to represent assets' lifetime and value-added process, following the international industrial standard IEC 6290. This axis brings two main concepts, i.e., type and instance, wherein "the type of an asset defines the sum of the properties which are characteristic for all instances of that particular asset" (DIN SPEC 9134, 2016, p. 14); and (3) hierarchy levels (i.e., product, field device, control device, station, work centers, enterprise, connected world) - used to assign functional models. It extends ISA-95 (IEC 62264) hierarchy levels by adding the product and field device levels at the bottom and connected world level at the top (Adolphs et al., 2015; Salazar et al., 2019; Moghaddam et al., 2018; Li et al., 2018). It is important to note that the point here "is not implementation, but solely functional assignment"(Adolphs et al., 2015, p.10).

RAMI4.0 introduces the I4.0 component as the basic element for I4.0 systems, consisting of an asset plus an administration shell that refers to an asset‘s data-warehouse. Moreover, it provides a unified model for the description of I4.0 components and enables the localization of existing industrial standards for implementing I4.0 systems.

2.2 Modeling and Simulation

Modeling and Simulation (M&S) is widely used in the domains of industrial engineering, operations, and supply chain management (Jahangirian et al., 2010; Frayret, 2011; Scheidegger et al., 2018). It refers to the process of designing a model of a real or hypothetical system for conducting computer simulation experiments to understand better the behavior and dynamics of a system (Scheidegger et al., 2018), enabling evaluating strategies to improve a system's design and operation, predict a system's performance, support decision-making and problem-solving (Frayret, 2011; Negahban and Smith, 2014). Indeed, M&S can be used for many purposes, such as prediction, proof, discovery, explanation, critique, prescription, and empirical guidance (Harrison et al., 2007). It is also considered a key enabling technology of I4.0 for managing complex systems (Kagermann et al., 2013).

In this context, some of the most common M&S methods include discrete-event simulation (DES), agent-based modeling and simulation (ABMS), and hybrid simulation (HS) that combines two or more simulation methods (Jahangirian et al., 2010; Negahban and Smith, 2014; Scheidegger et al., 2018; dos Santos et al., 2021). DES is a process-oriented approach "in which the state variables change only at those discrete points in time at which events occur" (Banks, 1998, p. 8). In contrast, ABMS is a decentralized approach, consisting of software agents with different levels of autonomy "that represents physical or logical objects in the system, capable of acting in order to achieve its goals, and being able to interact with other agents, when it does not possess knowledge and skills to reach its objectives alone" (Leitão, 2009, p. 982), played in a computer simulation. According to Siebers et al. (2010, p.207), true ABMS in operational research (OR) that focuses on decision support and/or problem-solving does not exist; combined applications of ABMS with DES "seems to be the way forward to tackle the problems in what becomes more an investigation into behavioral OR due to the recent shift of attention from manufacturing to service industry."

In line with that, there is increasing interest in HS to model complex systems since it enables the combination of extensive libraries built for single methods to represent a problem situation better and analyze it from different dimensions and perspectives (Jahangirian et al., 2010; Scheidegger et al., 2018; Brailsford et al., 2019; Mykoniatis and Harris, 2021; dos Santos et al., 2021). According to Brailsford et al. (2019), there are four main types of hybridization: (1) sequential – the output of one model is the input to another model; (2) enriching — narrow use of another method by one dominant; (3) interaction — the models interact cyclically without dominance; (4) integration — where it is not easy to distinguish the beginning of one method and the ending of another method. HS (ABMS + DES) provides a bottom-up approach to modeling systems, in which DES is used to represent the process flow and ABMS to substitute DES passive entities to active entities or entities with more complex behaviors, wherein models interact cyclically (Brailsford et al., 2019; Scheidegger et al., 2018). This approach enables capturing issues that emerge in the context of I4.0 since ABMS properties (e.g., autonomy, reactivity, proactiveness, social ability, reconfigurability, modularity, learning capacity) match I4.0 components and systems requirements (Contreras et al., 2017; Moghaddam et al., 2018; Salazar et al., 2019; Mykoniatis and Harris, 2021).

M&S involve different steps in an iterative process (Macal and North, 2010; Balci, 2012; Scheidegger et al., 2018; Brailsford et al., 2019). According to Brailsford et al. (2019), the DES project life-cycle can also apply to ABMS and HS. To that effect, there are three common phases to design a simulation model (Scheidegger et al., 2018), as illustrated in Fig. 2.2. The conception phase consists of developing and validating a conceptual model that captures the requirements of the problem (or system) under analysis, while the implementation phase consists of developing, verifying, and validating the computational model. In the analysis phase, computer experiments' results are analyzed, validated, and communicated to stakeholders.

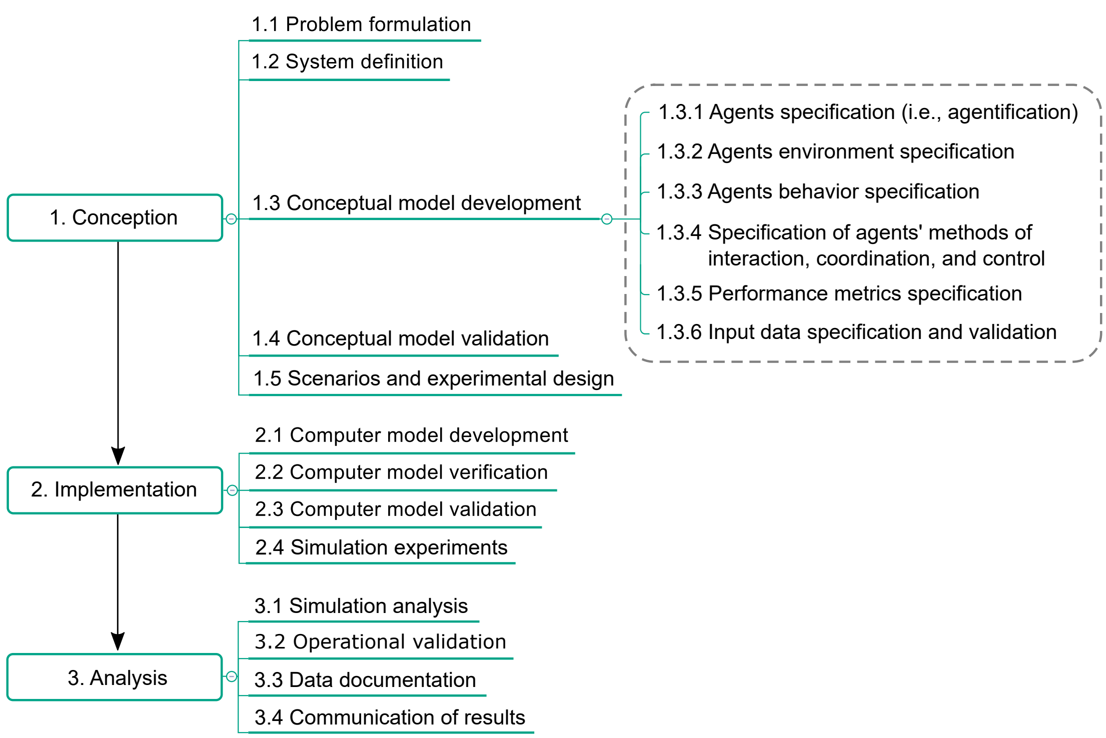

Figure 2.2 M&S project life cycle

Source: Adapted from Scheidegger et al. (2018), Balci (2012), and Macal and North (2010).

The main modeling tools used in the conception phase are the process flow diagram, the Business Process Model and Notation (BPMN), and the Unified Modeling Language (UML), or some of its variations, such as the Agent Unified Modeling Language (AUML) developed by the Foundation of Intelligent Physical Agents (FIPA) and the Object Management Group (OMG), where some of the most useful diagrams are: UML use-case diagram - used to capture the requirements and describe the functions and scope of the system to be modeled; UML class diagrams - used to describe the system's components and their static relationships; UML sequence diagrams - used to describe the interaction and communication between agents; and UML statecharts (also referred to as state machine diagrams) - used to describe the agents' behavior (Borshchev, 2013; Siebers and Onggo, 2014; Scheidegger et al., 2018).

Concerning the development of the computational models and analysis, there are several software tools available in the market, as listed in Scheidegger et al. (2018). A comprehensive comparative ABMS software tool list is also presented in Abar et al. (2017). However, most of them do not support HS. The software AnyLogic®, which is adopted in this thesis, is the leading multi-method general-purpose commercial simulation modeling tool available on the market, supporting both systems dynamics (SD), DES, and ABMS (Borshchev, 2013; Scheidegger et al., 2018; Brailsford et al., 2019). It applies to the manufacturing and logistics fields, and its main features include the moderate level of effort for the design and development of a model, high computational modeling strength, and scalability of the models, as characterized in Abar et al. (2017). Moreover, despite being a Java-based software, AnyLogic® supports artificial intelligence and can connect with Python through the Pypeline connector library. Furthermore, it supports the incorporation of solvers, such as the IBM CPLEX® and the open-source CLP for simulation-optimization models.

A simulation model, which can be stochastic or deterministic in nature, "should only be developed for a set of well-defined objectives," and its validity is determined in function of the purpose of the model (Sargent, 2013, p. 14). There are many statistical and non-statistical techniques for verification and validation of simulation models such as animation, comparison to other models, degenerated tests, sensitive analysis, event validity, trace, extreme condition tests, structured walkthrough, historical data validation, predictive validation, face validity, and operational graphics (Sargent, 2013; Macal, 2016; Scheidegger et al., 2018). It is worth mentioning that most of them are supported by AnyLogic® software. The main techniques used for conceptual and operational validation of DES, ABMS, and HS models are face validation, where stakeholders (e.g., domain experts) make subjective judgments about the model's sufficient accuracy, comparison of model' result to the existing system or other models, and animation (Frayret, 2011; Sargent, 2013; Scheidegger et al., 2018; Brailsford et al., 2019). At the same time, the main techniques used for conceptual model validation and computer model verification are face validation, structured walkthroughs, where the model is presented to peers to evaluate its correctness, and model tracing (Sargent, 2013).

2.3 Lean Manufacturing

The objective of a strategy is to turn an organization's capability into competitive advantages (Hallgren and Olhager, 2009). The strategies a business uses in its long-term planning help it achieve the objective of gaining value and sustainable competitive advantage in a dynamic external environment. Manufacturing strategies are a functional component that plays an essential role in a business unit's overall performance, mainly characterized by the way manufacturing resources are configured and deployed by a business unit to support the business strategy (Miller and Roth, 1994; Williams et al., 1995).

In line with that, after the seminal work of Womack et al. (1990), Lean Manufacturing (LM) gained broad popularity worldwide as a manufacturing strategy to increase companies' operational performance (e.g., cost, quality, flexibility, delivery), being successfully deployed by many organizations over different business sectors (Bhamu and Sangwan, 2014). Its emergence and historical evolution are discussed in detail in Holweg (2007). The essence of LM is based on five principles: specify the value, identify the value stream, continuous value flow, pull production, and continuous improvement (James and Jones, 1996). These principles can be implemented and evaluated through multiple LM practices and performance metrics, as described in Shah and Ward (2003, 2007) and Marodin and Saurin (2013).

LM is defined as "a socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability" (Shah and Ward, 2007, p. 791). There are seven wastes frequent in production processes that need to be addressed: overproduction, waiting, transport, inappropriate processing, excessive inventory, unnecessary motion, and defects (Ohno and Bodek, 1988). Non-utilized talent is an eighth waste that is often added to this list (Brito et al., 2019). According to Ohno and Bodek (1988), overproduction is the worst of all the seven wastes since making more than a company can sell disturbs a smooth flow of goods or services, the quality of the products and process productivity. Leading to long lead time, an excessive stock of raw material, work-in-process, and finished products, hiding defects, and adding artificial pressures on the work rate.

There is no standard LM implementation framework available in the literature (Bhamu and Sangwan, 2014). One of the main reasons for this may be because LM implementation depends on contextual factors, such as business sector, company size, and supply chain structure (Hallgren and Olhager, 2009; Shah and Ward, 2003). However, the set of LM practices and the order in which they are put in place are considered two critical factors to implement LM successfully (Sundar et al., 2014). Based on an exploratory survey, Sundar et al. (2014) selected a set of LM practices and proposed an LM roadmap, described as follows: (1) Implement the Value Stream Mapping (VSM) to analyze the process, identify improvement opportunities, and set the goals and work plan; (2) implement group technology and (3) cellular manufacturing to simplify production processes, facilitate the material flow, reduce work-in-process (WIP) and transportation time; (4) implement continuous flow, establishing one-piece flow; (5) Implement Jidoka for zero-defects, to ensure quality at the source; (6) use Kanban to implement pull-systems; (7) use Heijuka to level the production according to customer demand; and (8) deploy standardization (i.e., standardized work and process standardization) and continuous improvement. This process is executed iteratively.

Sundar et al. (2014) roadmap follows a similar sequence of steps to implement the VSM (Rother and Shook, 2003) and a similar pattern of LM practices in the Toyota Production System house (Jeffrey, 2004). Thus, it seems comprehensive enough to guide the implementation of LM in manufacturing companies. However, it is important to note that LM encompasses over 40 practices and there are many other LM implementation approaches (Shah and Ward, 2003, 2007; Marodin and Saurin, 2013; Rafique et al., 2019).

Despite that, Value Stream Mapping (VSM), also known as material and information flow mapping (Rother and Shook, 2003), is generally considered the first practice companies need to adopt to implement LM (Sundar et al., 2014; Andreadis et al., 2017; Buer et al., 2018; Rafique et al., 2019). Popularized by Rother and Shook (2003), Lean VSM became the main mapping tool used by researchers and practitioners to support the implementation of LM (Shou et al., 2017). It is originally a pencil and paper tool used to analyze the material and information flows from customer demand back to raw material, to identify wastes and improvement opportunities systematically and to set the goals to optimize the whole production process instead of making isolated improvements (Rother and Shook, 2003). VSM gives a broad view of the processes to stakeholders and helps improve communication, transparency, employees' capabilities, and coordination of continuous improvement activities (Andreadis et al., 2017; Shou et al., 2017; Rafique et al., 2019).

The application of Lean VSM usually follows a four step procedure: (1) select a product family; (2) draw the current-state map; (3) draw the future-state map; and (4) define a working plan (Rother and Shook, 2003). The future-state map is considered a guiding compass, driving the development of both flow and process Kaizen (i.e., continuous improvement activities). Rother and Shook (2003) proposed guideline questions to support the design of the future state map. To do so, quantitative process data (e.g., working time, number of operators, takt time, cycle time, lead time, change over time) are usually required, being embedded in both current and future-state map.

2.4 Summary of the literature review

According to Kagermann et al. (2013), there are eight priority areas for action to support the development of I4.0: (1) standardization and reference architecture; (2) managing complex systems; (3) a comprehensive broadband infrastructure for industry; (4) safety and security; (5) work organization and design; (6) training and continuing professional development; (7) regulatory framework; and (8) resource efficiency. So far, these are still priority areas that need further research and development to realize the I4.0 vision (Liao et al., 2017; Vieira et al., 2018; Tao and Zhang, 2017; Xu et al., 2018; Müller et al., 2018; Schneider, 2018; Adolph et al., 2020). Regarding priority number two, M&S is featured as a key enabling technology that needs further investigation (Kagermann et al., 2013).

Moreover, there is still a lack of understanding about I4.0 and methods and tools to help companies move towards I4.0 (Hofmann and Ruesch, 2017), especially for SMEs, which are still struggling to adhere to I4.0 (Moeuf et al., 2018). Most “SME oriented tools, frameworks and models do not extend beyond giving a current I4.0 readiness state of an organization” (Masood and Sonntag, 2020, p. 3). In line with that, the systematic literature review and empirical survey about managerial challenges of I4.0 conducted by Schneider (2018) revealed eighteen issues, classified in six clusters, including strategy and analysis, planning and deployment, and change management and leadership. Their research agenda suggests a strong need for practice-enhancing research – encompassing the development and assessment of use cases; and knowledge-enhancing research – concerning implementation strategies and roadmaps.

With the advancement of I4.0 and its enabling technologies, researchers started to investigate the enabling effects of I4.0 on LM and vice versa, suggesting that its integration or concurrent adoption may enhance companies’ operational performance (Sanders et al., 2016; Tortorella and Fettermann, 2018; Tortorella et al., 2019; Buer et al., 2018, 2021a; Matteo et al., 2019; Shahin et al., 2020a; Rosin et al., 2020). Indeed, some authors consider LM as a prerequisite for implementing I4.0 (Buer et al., 2018; Ciano et al., 2021). According to Ciano et al. (2021, p. 1339), if LM is not implemented before introducing new technologies and digital innovation related to I4.0, there is a higher risk that “the results would be just a digitalization of existing wastes”. In line with this, as discussed by Buer et al. (2018), on the one hand, if applied to efficient operations, automation technologies may amplify efficiency. On the other hand, if applied to inefficient operations, automation technologies may amplify inefficiency.

In accordance with that, much of the data necessary to calculate the 45 LM performance metrics listed in Marodin and Saurin (2013) are collected manually or gathered from different information systems, and the calculation processes to convert those data into usable information often require a lot of effort (Meudt et al., 2017). Companies can apply I4.0 technologies such as big data analytics to automate this conversion process (Wagner et al., 2017). If combined with other technologies, such as IoT and CPS, much of the data collection and analysis process could be automated to provide stakeholders a VSM and LM performance metrics in real-time (Sanders et al., 2016; Wagner et al., 2017; Buer et al., 2018). It would undoubtedly advance the identification of wastes and improvement opportunities in production processes, as well as reduce problem-solving response time (Wagner et al., 2017; Meudt et al., 2017).

Sanders et al. (2016) evaluated the impacts of I4.0 in ten dimensions of LM, suggesting that I4.0 technologies can enhance the performance of LM systems. For example, IoT and big data analytics can be employed to track goods wirelessly across the value chain and provide smart order reallocation to reduce lead time, eliminating problems related to the insufficient status of goods transported, inventory errors, and unforeseen transportation delays. Moreover, artificial intelligence will allow companies to reduce setup time, lot size, and downtime drastically since it enables machines self-optimization, self-maintenance assessments, and the creation of predictive maintenance systems (Sanders et al., 2016). Many other examples about the empowering effect of I4.0 on LM (e.g., CPS just-in-time delivery system) are provided in Hofmann and Ruesch (2017), Cimino et al. (2019), and Rosin et al. (2020).

Cimino et al. (2019) gives some insights on how LM can support I4.0, establishing relationships between many LM practices and I4.0 technologies. For example, they suggest that Lean VSM can be extended to support I4.0 initiatives in companies. This assertion is supported by other authors (Lugert et al., 2018; Buer et al., 2018; Pagliosa et al., 2019; Uriarte et al., 2020). From Ciano et al. (2021), Lean VSM enables vertical integration that is one of the main principles of I4.0 since it can be used to define value-adding activities to be standardized and digitalized. In line with this, Lugert et al. (2018) conducted a literature review and surveyed 170 Lean experts about the potentials and development needs of VSM. Their findings suggest M&S as a key technology to enhance VSM and extend its use to the context of I4.0. Other authors also argue that Lean VSM combined with M&S technologies has the potential to support companies' transition toward I4.0, but it is still under-explored in the literature (Buer et al., 2018; Uriarte et al., 2020; Pagliosa et al., 2019; Ciano et al., 2021).

Indeed, the intersection of LM with I4.0 is an emerging research area with many still-open issues as revealed by the systematic review on the links between I4.0 and LM conducted by Buer et al. (2018), which identified gaps into five research areas: (1) impact of I4.0 on soft LM practices; (2) facilitating effects of LM on I4.0 implementation; (3) performance implications of I4.0 and LM integration; (4) environmental factors' effects on an I4.0 and LM integration; and (5) implementation framework for moving towards an I4.0 and LM integration.

CHAPTER 3 METHODOLOGY

"Research is a formalized curiosity.
It is poking and prying with a purpose"
– Zora Neale Hurston

This section describes the research methodology used to achieve the objectives and answer the research questions of this Ph.D. thesis presented in Sections 1.3 and 1.4. This research was developed in collaboration with a College Centre for the Transfer of Technologies (CCTT) located in Quebec, Canada, following a triple helix collaboration approach, which involves academic institutions (i.e., college, university), government, and industry.

3.1 Research classification

Regarding its nature, this research is classified as applied research, whose aim is to generate knowledge for practical applications. From the point of view of how to approach the problem, it adopts mixed methods, combining qualitative and quantitative approaches. From the standpoint of technical procedures, this research follows the Design Science Research (DSR), as described in Hevner et al. (2004), which is a well-accepted research paradigm in information systems and engineering domains to support the development of new artifacts (e.g., constructs, models, methods, instantiations) "that can be applied to the solution of real-world problems or to enhance organizational efficacy" (Peffers et al., 2018, p. 129).

3.2 Research design

The research design follows Hevner et al. (2004) framework and guidelines for conducting DSR, executed iteratively and progressively, comprising multiple design cycles of artifact development, evaluation, and refinement, and research methodologies. As summarized in Fig. 3.1, a design cycle begins with awareness of business needs or a problem, as perceived and defined by the researcher. Then, possible solutions are derived from the existing knowledge base of the problem space, composed of foundations (e.g., constructs, theories, frameworks, methods, models) and methodologies. After that, assessment and refinement processes are performed. The latter is often described in future research directions and recommendations, performed in a new design cycle (Hevner et al., 2004).

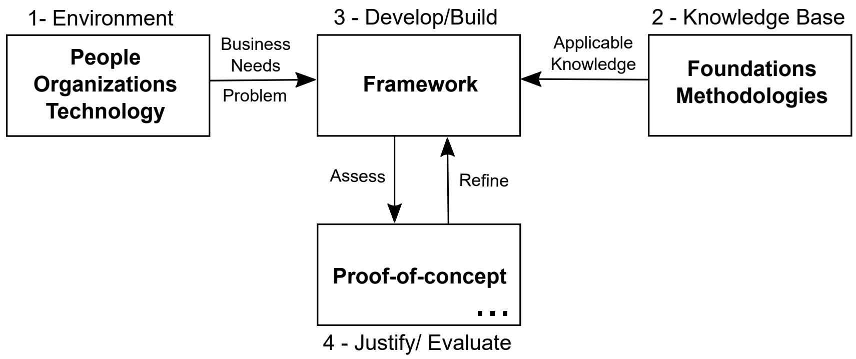

Figure 3.1 Design Science Research framework

Source: Adapted from Hevner et al. (2004)

In line with that, the research was divided into three complementary studies, framed into three original contribution articles, presented in Chapters 4, 5, and 6. The overall research design of this thesis is summarized in Fig. 3.2. It starts with an exploratory study (i.e., systematic literature review) to characterize the I4.0 constructs and the development of simulation-based research in I4.0, summarized into an analytic framework, used as a basis for the other studies. Next, a framework for identifying and analyzing I4.0 scenarios is proposed to help companies plan their transition to I4.0. It is evaluated through a use cases survey and a proof-of-concept case developed in a CCTT located in Quebec, Canada. Then, a new framework to support I4.0 initiatives in manufacturing companies is presented to complement the previous contribution. The latter is mainly evaluated through a proof-of-concept case developed in a Canadian SME from the furniture and related product manufacturing sector.

3.3 Research activities

DSR is not a method with rigid rules but rather a strategy that can be operationalized in different ways (Van Aken et al., 2016). Since this thesis is structured by articles, the research activities are split into three studies (see overview in Fig. 3.2). The first study, presented in Chapter 4, adopted the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) methodology described in Moher et al. (2009), widely used across different research fields, including I4.0 (Liao et al., 2017; Buer et al., 2018). It consists of a 27-item checklist and a four-phase flow diagram (i.e., identification, screening, eligibility, included) to help authors improve the development and reporting of robust systematic reviews and meta-analyses. In addition, the snowball sampling technique (Wohlin, 2014) that uses an article's reference list (backward snowballing) and the citations to the article (forward snowballing) was applied in order to prevent relevant studies from being missed. The research was conducted using the electronic databases Web of Science and Scopus.

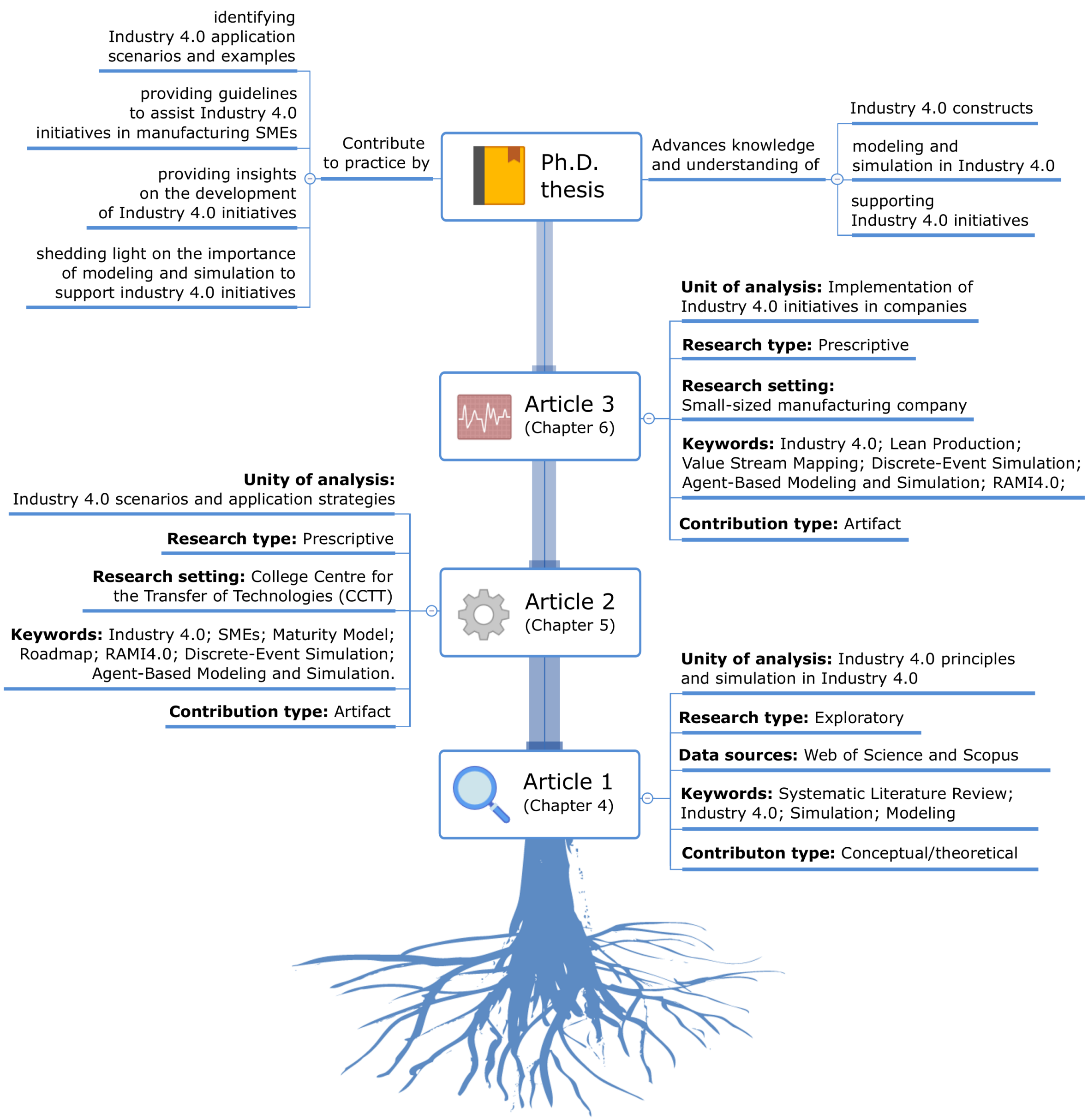

Figure 3.2 The structure tree of the thesis by article rooted in design science research

In the second study, presented in Chapter 5, a simple natural language generation (NLG) approach, consisting of a text-to-text generation by filling gaps in a template (composed of slots and rules) predefined by a knowledge expert was adopted to generate the I4.0 scenarios (McRoy et al., 2003; Gatt and Krahmer, 2018). It also involved a use cases survey (Larsson, 1993), conducted using the Web of Science, Scopus, and Google Scholar electronic databases, and HS (DES + ABMS), used to test the overall proposed framework. The data collected for the development of the framework and proof-of-concept case included: direct observation during participation in CCTT weekly meetings related to I4.0 initiatives for six months to capture business needs and refine the proposed framework; secondary data (e.g., I4.0 maturity assessment) from four manufacturing SMEs assisted by the CCTT to support the case selection and contextualization for enabling posterior technology transfer; application of the self-assessment maturity model proposed by Lichtblau et al. (2015) with project managers of the CCTT; and process and manufacturing data from the CCTT living lab (also referred to as mini-factory), which mimic many industrial-scale situations.

The third study, presented in Chapter 6, involved mainly modeling and simulation methodologies (i.e., DES, ABMS, HS). It also adopted the ADAptive holonic COntrol aRchitecture (ADACOR) for distributed manufacturing systems proposed by Leitão and Restivo (2006), which is based on the Product-Resource-Order-Staff-Architecture (PROSA) for holonic manufacturing systems (Van Brussel et al., 1998), and the RAMI4.0 (DIN SPEC 9134, 2016). The proof-of-concept case was developed in a manufacturing SME part of the network of companies assisted by the CCTT investing in I4.0. The three studies adopted the Unified Modeling Language (UML) for conceptual modeling, and the last two studies adopted the AnyLogic multimethod software for building the computational models.

3.4 Certificate of ethical acceptability

An ethical certificate was requested during the Ph.D project. The ethics certificate from Polytechnique Montréal Research Ethics Board (REB) was granted on December 1, 2020 (certificate #CER-2021-26-D).

3.5 Research structure

This Ph.D. thesis is built up of three interrelated studies, later converted into scientific articles presented in Sections 4, 5, and 6. An overview of the structure of the main body of this Ph.D. thesis is presented in Fig 3.2. It also includes a general discussion presented in Section 7 to summarize the main results of these three studies, explaining in more detail how they are tied together and providing a perspective of the thesis as a whole. Lastly, a conclusion is presented in Section 8 to highlight the main contributions and limitations of this thesis and provide directions for future research. It is worth mentioning that this Ph.D. thesis was configured in accordance with the guide for presenting theses and dissertations by articles of Polytechnique Montréal and best practices identified in the literature (Kubota et al., 2021; Lewis et al., 2021; Lovitts, 2007; Badley, 2009).

CHAPTER 4 ARTICLE 1: SIMULATION IN INDUSTRY 4.0: A STATE-OF-THE-ART REVIEW

"One can state, without exaggeration, that the observation of and the search for similarities and differences are the basis of all human knowledge"
– Alfred Nobel

This chapter presents a systematic literature review focusing on identifying the main constructs of Industry 4.0 and characterizing the current state of the art of simulation in Industry 4.0. The manuscript contained in this chapter was co-authored[1] with my research director, Prof. Fabiano Armellini, and my co-research director, Prof. Luis Antonio de Santa Eulalia. I am the first author, and my contribution is estimated at 90%. The manuscript was submitted to the journal Computers & Industrial Engineering on January 22, 2020, accepted on September 17, 2020, after a double-blind peer-review process, and published on September 21, 2020. The article is cited as follows: de Paula Ferreira, W., Armellini, F., and De Santa-Eulalia, L. A. (2020). Simulation in industry 4.0: A state-of-the-art review. Computers & Industrial Engineering, 149:106868. doi: 10.1016/j.cie.2020.106868.

[1] **Author contributions:** William de Paula Ferreira: Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. Fabiano Armellini: Conceptualization, Supervision, Validation, Funding acquisition, Writing - review & editing. Luis Antonio De Santa-Eulalia: Conceptualization, Supervision, Validation, Writing - review & editing.

Simulation in Industry 4.0: A state-of-the-art review

Authors: William de Paula Ferreira, Fabiano Armellini, Luis Antonio de Santa-Eulalia

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Abstract: Simulation is a key technology for developing planning and exploratory models to optimize decision making as well as the design and operations of complex and smart production systems. It could also aid companies to evaluate the risks, costs, implementation barriers, impact on operational performance, and roadmap toward Industry 4.0. Although several advances have been made in this domain, studies that systematically characterize and analyze the development of simulation-based research in Industry 4.0 are scarce. Therefore, this study aims to investigate the state-of-the-art research performed on the intersecting area of simulation and the field of Industry 4.0. Initially, a conceptual framework describing Industry 4.0 in terms of enabling technologies and design principles for modeling and simulation of Industry 4.0 scenarios is proposed. Thereafter, literature on simulation technologies and Industry 4.0 design principles is systematically reviewed using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology. This study reveals an increasing trend in the number of publications on simulation in Industry 4.0 within the last four years. In total, 10 simulation-based approaches and 17 Industry 4.0 design principles were identified. A cross-analysis of concepts and evaluation of models' development suggest that simulation can capture the design principles of Industry 4.0 and support the investigation of the Industry 4.0 phenomenon from different perspectives. Finally, the results of this study indicate hybrid simulation and digital twin as the primary simulation-based approaches in the context of Industry 4.0.

Keywords: Discrete-Event Simulation, Agent-Based Modelling and Simulation, System Dynamics, Virtual Reality, Augmented Reality, Petri Nets, Virtual Commissioning.

[2] Available in de Paula Ferreira et al. (2020).

4.1 Introduction

The Industry 4.0 (I4.0), i.e., the Fourth Industrial Revolution, is a term conceived at the Hannover Fair in 2011 as part of Germany's long-term strategy to strengthen the competitiveness of its manufacturing sector (Liao et al., 2017). From *Industrie 4.0* working group, it "will lead to the emergence of dynamic, real-time optimized, self-organizing value chains that can be optimized based on criteria such as cost, availability, and resource consumption" (Kagermann et al., 2013, p. 20). After 2013, I4.0 gained worldwide recognition and became a hot topic in scientific literature (Lasi et al., 2014; Liao et al., 2017; Xu et al., 2018). Moreover, it was the main subject of discussion at the 2016 World Economic Forum owing to its high relevance to the manufacturing sector (Schwab, 2017). A global survey with over 2,000 participants proposes that approximately 5% of a companies' annual revenue will be invested in digitalization projects. In turn, companies expect to reduce their operational costs by 3.6% per year (PwC, 2016). These studies reinforce the argument that the digitalization of production systems will drive innovation over the next decades (Kagermann et al., 2013).

There is no standard definition for the term I4.0 in literature (Liao et al., 2017). Particularly, over a hundred definitions of I4.0 have been developed (Moeuf et al., 2018). I4.0 is often described as a set of design principles and enabling technologies to guide researchers and practitioners to implement I4.0 scenarios in companies (Hermann et al., 2015; Ghobakhloo, 2018). Overall, I4.0 is considered as a new socio-technical paradigm that depends on further development, access, and integration of information and communication technologies (ICT) with automation technologies to promote end-to-end systems integration across the entire value chain (Kagermann et al., 2013). It "is a collective term for technologies and concepts of value chain organization" (Hermann et al., 2015, p. 11), having implications on value creation, business models, services, and work organization (Kagermann et al., 2013; Schwab, 2017; Xu et al., 2018).

A revolutionary aspect of I4.0 is the accessibility to its enabling technologies, made possible by the lowering price and widespread use of sensors throughout value chains (Dalenogare et al., 2018), which aids in removing barriers to effective supply chain integration and management (Cragg and McNamara, 2018; Ralston and Blackhurst, 2020; Hofmann et al., 2018). Nonetheless, from Li et al. (2017a), the novelty of I4.0 is classified into three axes: (1) technological advances and integration; (2) scaling of the access and robustness of the internet, and (3) convergence of digital, physical, and biological technologies together with its widespread and influence in the dynamics of business, economy and social development. This is consistent with the definition of I4.0 provided by Schwab (2017). Schneider (2018) also explained that the feasibility of I4.0 differentiates it from previous initiatives because of the increasing number of available technologies, the growth of companies' digital capabilities, and intra and cross-company integration through a complex value chains network, consistent with Hofmann and Ruesch (2017) and Xu et al. (2018).

Several initiatives related to I4.0 have been launched worldwide to strengthen the competitiveness of the manufacturing sector, predominantly through bi- or tripartite collaboration from a triple helix (university-industry-government) collaboration (Liao et al., 2017). Examples of these initiatives include the manufacturing USA program, also known as national network for manufacturing innovation (NIST, 2019); Canada's advanced manufacturing supercluster (Elci et al., 2019); the project evolution of networked services through a corridor in Quebec and Ontario for research and innovation - ENCQOR (ISED, 2019); German high-tech strategy 2020 (Kagermann et al., 2013); factories of the future in the European union's (Liao et al., 2017); and made in China 2025 (Xu et al., 2018).

Although some literature report several ongoing projects, I4.0 is nonetheless in its infancy, and most examples are either in the planning stage or are pilot projects (Liao et al., 2017; Xu et al., 2018; Alcácer and Cruz-Machado, 2019). Furthermore, research on risks, costs, revenue potential, and implementation barriers of I4.0 is scarce. Additionally, there is a lack of support to companies desiring to use this new social-technical paradigm (Hofmann and Ruesch, 2017). In this context, simulation techniques play major roles because they offer the possibility to evaluate multiple I4.0 scenarios through the development of planning and exploratory models of complex systems, which can aid addressing partly the aforementioned problems (Kagermann et al., 2013; Lugert et al., 2018).

Modeling and simulation are relevant techniques in the fields of industrial engineering, operations, and supply chain management (Shafer and Smunt, 2004; Negahban and Smith, 2014; Scheidegger et al., 2018). It is an enabling technology of I4.0 for managing complex systems (Ghobakhloo, 2018; Moeuf et al., 2018; Alcácer and Cruz-Machado, 2019). Moreover, an empirical research (Jeong et al., 2018) and patent analysis (Han et al., 2018) proposed modeling and simulation as critical technologies to produce innovations and develop the I4.0.

In manufacturing and logistics systems, which is the primary focus of this study, modeling and simulation denote a set of methods and technological tools that allows the experimentation and validation of products, processes, systems design and to predict system performance. It also supports decision making, education and training, aiding to reduce costs and development cycles (Negahban and Smith, 2014). Moreover, modeling and simulation are robust methods in science and developing theories (Davis et al., 2007), which can be used for different purposes, such as prediction, proof, explanation, prescription, and empirical guidance (Harrison et al., 2007).

Furthermore, the application of simulation technologies is a component of industry leaders' initiatives and strategy for implementing I4.0, such as General Electric's (GE) brilliant factory (Thilmany, 2017), and Siemens' digital factory (Shih, 2016), which addresses manufacturing plant virtualization, visualization, and simulation. Siemens and GE hold different patents related to new simulation techniques (Tao et al., 2018b). From Tao et al. (2018b), examples of industrial applications include the use of simulation by Siemens for systems planning, operation, and maintenance; the application of simulation by GE for asset management and optimization; and the employment of simulation by Airbus to monitor and optimize production processes. In addition, most leading simulation software vendors (e.g., AnyLogic, MathWorks, Siemens, Arena, Dassault Systèmes, Autodesk, Flexin, Simul8, Aspen Technology, AVEVA, Simio) are investing in the development of commercial solutions for I4.0 (Martin, 2019; AnyLogic, 2020), following the increasing interest from companies in modeling and simulation technologies (Deloitte, 2018).

Nevertheless, advancements in I4.0 and its enabling technologies introduce new challenges to the field of simulation owing to the increasing complexity of systems to be modeled (Vieira et al., 2018; Tao et al., 2018a; Martin, 2019; Zhou et al., 2019; Uriarte et al., 2020). Therefore, this study aims to investigate the state-of-the-art of research at the intersection between the emerging field of Industry 4.0 and the field of simulation. The research question (RQ) addressed in this study are the following: RQ1 - What are the simulation-based approaches being employed in the context of I4.0?; RQ2 - What are the purposes, empirical nature, and applications area of studies on simulation in I4.0?; RQ3 - What are the design principles of I4.0?; RQ4 - Which I4.0 design principles are captured by each simulation-based approach?

Although there are several reviews on simulation, they either are not in the context of I4.0 (Jahangirian et al., 2010; Negahban and Smith, 2014), focus on a specific simulation technique (Rodič, 2017; Vieira et al., 2018; Tao et al., 2018b), or have a different scope/design from this research (Mourtzis, 2019). To the best of our knowledge, this is the first article providing a general overview and comparison between simulation technologies and design principles of I4.0. Furthermore, the time considered in this study extends the dates of coverage of existing reviews, including more recent publications. Additionally, whereas comparing the reference list of this study with the reference lists of existing review articles, through a bibliographic coupling analysis (Van Eck and Waltman, 2014), it overlaps maximum in 6%, indicating that this study introduces new and important insights for those striving to understand the state-of-the-art of research at the intersection of I4.0 domain with the simulation domain.

The main contributions of this study are threefold. First, it presents a broad coverage of the specialized literature using a quantitative and qualitative approach, identifying the simulation approaches used relative to the I4.0. Second, it extends the list of I4.0 design principles provided by Ghobakhloo (2018) and establishes a link between simulation technologies and I4.0 design principles. Third, it provides a comprehensive classification of simulation studies relative to I4.0.

The remainder of this study is organized as follows. Section 4.2 describes the research methodology used to review the literature. Section 4.3 and 4.4 present the quantitative and quantitative analyses, respectively. Section 4.5 presents the discussion. Section Section 4.6 introduces the limitations and opportunities for future research. Finally, conclusions are outlined in Section 4.7.

4.2 Methodology

4.2.1 Conceptual framework

Fig. 4.1 presents the conceptual framework to guide the systematic review, represented as a unified modeling language (UML) class diagram, which describes the system's components and the different types of static relationships among them (Bersini, 2012). As shown in Fig. 4.1, I4.0 can be described in terms of its design principles and enabling technologies (Hermann et al., 2015, 2016; Ghobakhloo, 2018). The simulation characterizes one or more enabling technologies of I4.0 (Kagermann et al., 2013; Ghobakhloo, 2018), which can be used to evaluate multiple I4.0 scenarios (Houston et al., 2017; Martin, 2019; Tao et al., 2018a; Gajsek et al., 2019).

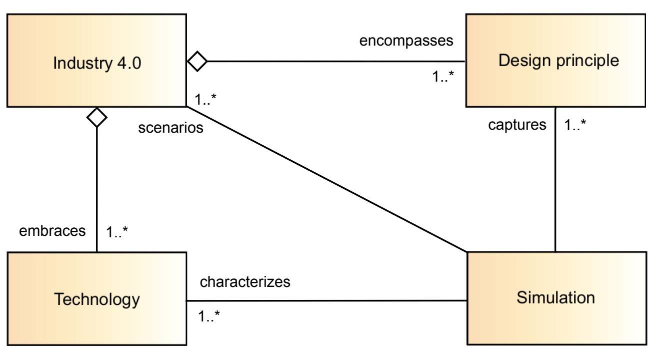

Figure 4.1 Conceptual framework

To better understand these relationships in Fig. 4.1, the design principles that serve as the foundation of I4.0 and existing simulation-based approaches used relative to I4.0 will be systematically reviewed. Simulation techniques serve different purposes (Harrison et al., 2007) and apply to different areas (Jahangirian et al., 2010), which can enable easy examination of the I4.0 phenomenon from different perspectives. Therefore, the uses of simulation, the application areas, and the relationship between the simulation approaches and I4.0 design principles will also be investigated.

4.2.2 The systematic review strategy

To ensure a robust and rigorous systematic literature review, the preferred reporting items for systematic review and meta-analysis (PRISMA) methodology (Moher et al., 2009), consisting of a 27-item checklist and a four-phase flow diagram (see Fig. 4.2), was adopted. From Moher et al. (2009), the PRISMA's checklist provides guidelines to conduct a systematic literature review and the PRISMA flow chart describes the information flow through the different phases of the systematic literature review (i.e., identification, screening, eligibility, inclusion). With thousands of citations on the web of science, Scopus, and Google scholar, this approach is widely used across different research fields to guide the development of systematic reviews, including I4.0 (Liao et al., 2017).

Sampling

The data collection follows a two-phase process to enable the cross-analysis of concepts (see Fig. 4.2). The first phase systematically identifies studies that use simulation-based approach relative to I4.0, whereas phase two systematically identifies publications that analyze or review the design principles of I4.0. The search protocol adopted in each phase were built in three steps (see Table 4.1).

Table 4.1 Search protocol

SP1	Data source:	Web of Science and Scopus
	Search string:	"simulation" AND ("model*" OR "framework") AND ("Industry 4.0" OR "Industrie 4.0" OR "Fourth Industrial Revolution" OR "4th Industrial Revolution")
	Search fields:	Title, abstract, and keywords
	Period:	From 2011 to December 31, 2019
	Language:	English
	Document:	Journal articles
SP2	Data source:	Web of Science and Scopus
	Search string:	("design principle*" OR "requirement*") AND ("Industry 4.0" OR "Industrie 4.0" OR "Fourth Industrial Revolution" OR "4th Industrial Revolution") AND ("literature review" or survey or state-of-the-art)
	Search fields:	Title, abstract, and keywords
	Period:	From 2011 to December 31, 2019
	Language:	English
	Document:	All types

First, the electronic data sources Web of Science Core Collection and Scopus, broadly covering the management and engineering research literature, were selected. Second, the search string was constructed based on the objectives of the research. Third, four eligibility criteria were applied: (1) date of coverage: the search period ranges from the beginning of 2011, with the emergence of the term Industry 4.0 (Liao et al., 2017), to December 31, 2019; (2) Search fields: title, abstract, or keywords of articles in the data sources; (3) Document types: in the first search protocol, only journal articles were included as they were considered more reliable owing to the rigor of the evaluation process and because they predominantly provide significant details about the methodology, which is essential to the development of this study. However, in the second search protocol, all types of documents were considered; (4) Language: consider only studies published in English.

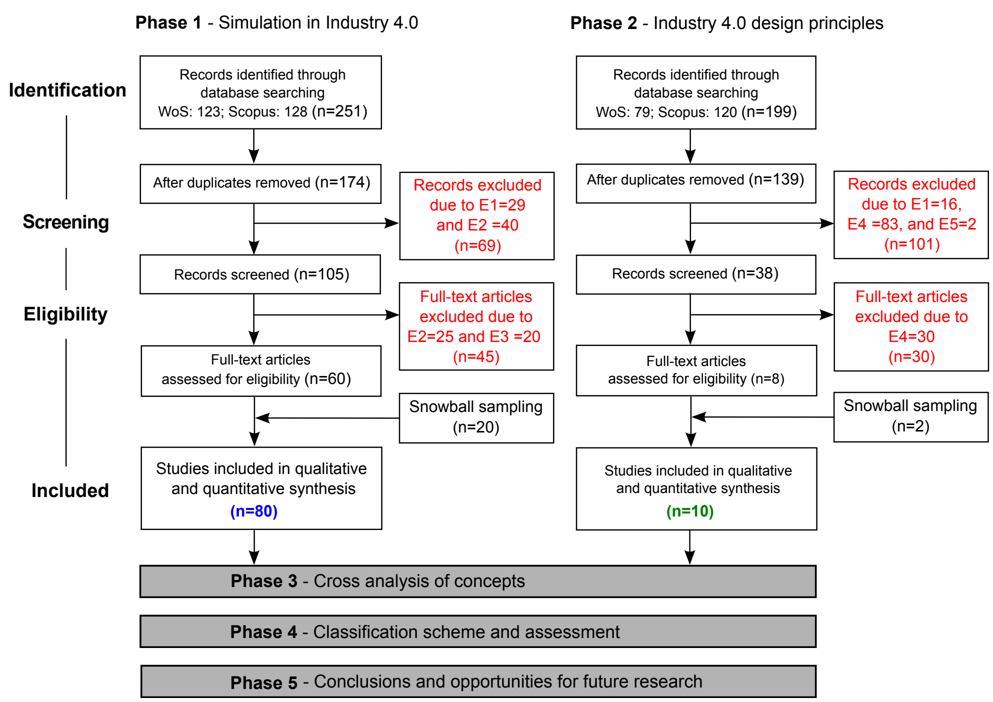

Figure 4.2 Systematic review strategy

After defining the search strategy, articles were identified, screened, and assessed for eligibility, to develop the final sample. A summary of the systematic review strategy, based on PRISMA methodology, is exhibited in Fig. 4.2.

The identification phase consisted of applying the search protocol in each data source, combining the articles into a single database, and removing duplicates using EndNote X9 and double-checking references. The screening phase consisted of analyzing the title, abstract,

Table 4.2 Inclusion and exclusion criteria with the total number of occurrences

Criteria	Description	Total occurrences	
		Phase 1	Phase 2
Exclusion (E)	E1: Industry 4.0 or Simulation is used only as a keyword, example fact, or cited expression.	29	16
	E2: Does not fit with the scope of the research.	65	N/A
	E3: Industry 4.0 or Simulation is only used to describe some challenges, trends, or recommendation.	20	N/A
	E4: The paper does not focus on the analysis or review of Industry 4.0 design principles.	N/A	113
	E5: Full-text could not be assessed or is not in English.	N/A	2
Inclusion (I)	I1: Simulation and Industry 4.0 are part of the main research effort.	80	N/A
	I2: The paper analyze or review the design principles of Industry 4.0	N/A	10

and keywords of articles in the sample, applying the exclusion criteria in Table 4.2. In the eligibility phase, the remaining full-text articles remaining in the sample were assessed for qualification. Only articles matching the inclusion criteria in Table 4.2 were accepted in the sample. Next, the backward and forward snowball sampling technique was applied to these articles to determine if any relevant references was missed in the sample. Snowballing is an important search technique to develop systematic review studies (Wohlin, 2014). It uses an article's reference list (backward snowball sampling) or the citations to the article (forward snowball sampling) to identify additional references to include in the sample of articles to be reviewed (Wohlin, 2014). Finally, in the inclusion phase, articles in the sample after eligibility analysis plus articles identified through the snowball sampling were included in the quantitative and qualitative analysis.

Phase 1 initially resulted in 251 articles. After duplicate removal, the sample reduced to 174 articles. The titles, abstracts and keywords were thereafter analyzed and exclusion criteria E1 and E2, set out in Table 4.2 were applied, reducing the sample from 174 to 105 articles. At this stage, the 62 articles excluded owing to E2 occurred mainly because they focused on other areas (e.g., energy, healthcare, construction, telecommunication), alternate to on manufacturing or logistics systems. After assessing the full text of the articles, the other 45 articles were excluded owing to E2 and E3, resulting in a sample with 60 articles. By performing the snowball sampling, 20 additional articles were identified. Hence, a total of 80 articles were included in the final sample for the quantitative and qualitative analysis. A third researcher, an expert in the field, double-checked the reference lists (articles excluded and included in the sample) to reduce potential bias. The underlying principle was, whenever a disagreement about the inclusion or exclusion of an article occurs (which were very few cases), we appended the article to the sample to prevent missing possible relevant studies in the sample.

In phase 2, we repeated the four step procedure in Fig. 4.2 to identify studies describing the principles of I4.0, resulting in a sample of 10 articles, included in qualitative analysis. Here, most of the 113 articles were excluded owing to E4 because they used design principles or requirements only as a keyword, cited expression, or example fact, and did not focus on the analysis or review of the design principles of Industry 4.0.

Data analysis

Adhering to the PRISMA guidelines (Moher et al., 2009), this research uses a mixed-method systematic review, combining quantitative and qualitative approaches. Accordingly, the data analysis was divided into two stages. First, we performed a quantitative synthesis through graphical and tabular methods of descriptive statistics. Thereafter, we conducted a qualitative content analysis, which involves decontextualization, recontextualization, categorization, and compilation of data (Bengtsson, 2016).

Overall, the research design is divided into four phases, as depicted in Fig. 4.2. Firstly, studies at the intersection of I4.0 and simulation fields are selected to identify the simulation-based approaches used relative to I4.0. Secondly, reviewed articles related to I4.0 are analyzed to identify the design principles of I4.0, i.e., essential constructs for the development of I4.0 models. Now, a quantitative analysis of the simulation-based studies is performed, and the simulation approaches in I4.0, and the design principles of I4.0, introduced. Thirdly, a cross-analysis of concepts that establishes the relationship between the simulation-based approaches and the design principles of I4.0 is presented. Next, a classification scheme (coding) with five categories, subdivided into 61 subcategories, is developed to guide further content analysis. The 80 articles included in the final sample of phase 1 were next classified, and the results reported. Lastly, gaps and opportunities for future research are discussed.

4.3 Quantitative analysis

The sample size of phase 1 comprises of 80 journal articles, used for both quantitative and qualitative analysis (see Appendix A). Fig. 4.3 displays the distribution of these publications over time, showing an upward trend in the number of scientific publications in the fields of I4.0 and simulation. It is observed that more than 70% of the articles were published in the last two years. Fig. 4.3 indicates that the research field at the intersection of the I4.0 domain with the simulation domain is new and under-explored, considering the potential of simulation to develop I4.0 and vice versa, as highlighted by the academic, and industry professionals and other organizations (Kagermann et al., 2013; Shih, 2016; Thilmany, 2017;

Lugert et al., 2018; Tao et al., 2018a; Martin, 2019; AnyLogic, 2020).

The geographical distribution of the publications is presented in Fig. 4.4. The top 10 most frequent were considered. Another 25 countries were represented in the sample, with up to two publications. The institution and location information from the affiliation of all authors of each article was considered. Therefore, a publication with authors from different institutions and countries were computed separately. In total, the 80 articles analyzed involved 322 authors, 161 institutions, and 35 countries, with an average of 4.03 authors per article and a standard deviation of 1.55. Almost 70% of the research articles were co-authored by four or more researchers. In total, 61 articles (78.75%) involved one or more institutions of a single country, whereas 17 articles (21.25%) involved institutions in different countries, suggesting that it remains considerable room for international collaboration. Considering the distribution by continent, we find: Europe (54 articles; 66%); Asia (34 articles; 41%); North America (7 articles; 9%); and South America (6 articles; 8%). There is a higher concentration of publications linked to European institutions, mainly from Germany, Italy, and the UK, following a similar pattern of I4.0 publications, as presented in Liao et al. (2017).

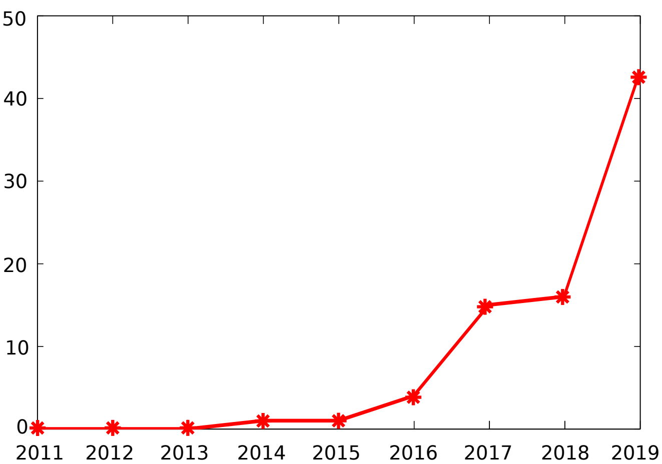

Figure 4.3 Number of publications per year

The keyword analysis is important to initially identify the primary constructs addressed in the content of the studies. In total, 871 keywords were collected from the 80 studies. Table 4.3 presents the 10 most common keywords, excluding the two used in the query (i.e., simulation, Industry 4.0) and the ratio based on the absolute number (n) of articles in the sample.

The keywords in Table 4.3 suggests that most of the studies (62%) are within the manufacturing context, which is in the scope of this study. Furthermore, it indicates three core enabling technologies of I4.0, i.e., the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Big Data, as described by Kagermann et al. (2013). In addition, it indicates that: 35% of

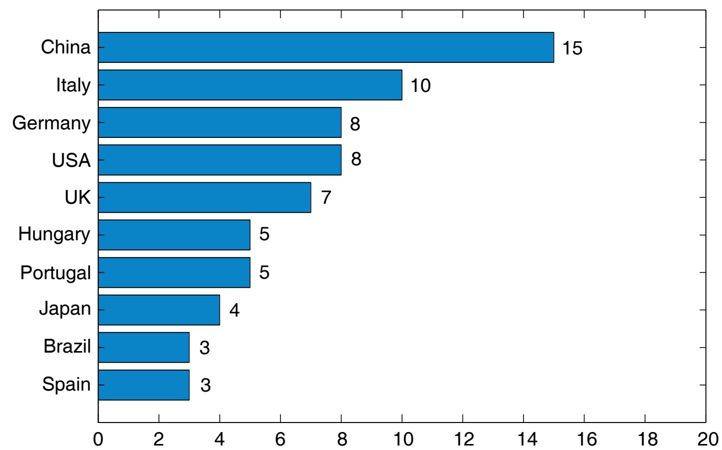

Figure 4.4 Geographic distribution of publications

the studies in the sample may adopt agent-based modeling and simulation (ABMS) or multi-agent systems (MAS), considering that both terms are often used interchangeably (Barbati et al., 2012); that 17% of studies may address digital twin (DT); 16% virtual reality; and 10% discrete-event simulation (DES). This analysis also indicates the other three simulation approaches: system dynamics (3%), augmented reality (3%), and hybrid simulation (5%).

Table 4.3 Keywords frequency analysis

Keyword	n	%
Manufacturing	53	66.3
Cyber-Physical Systems	41	51.3
Agent-Based Simulation	30	37.5
Decision Making	21	26.3
Smart manufacturing	17	21.3
Digital Twin	15	18.8
Virtual Reality	14	17.5
Internet of Things	11	13.8
Discrete Event Simulation	9	11.3
Big Data	8	10.0

The articles were published in 29 different scientific journals (see Table 4.4), covering the leading journals of industrial engineering and simulation fields, based on the journal citation reports (JCR) and SCImago journal rank (SJR) of 2019. Table 4.4 considers initially the total number of articles per journal, followed by the journal's impact factor (IF), based on the JCR, and SJR. The number of publications per journal per year and the proportion of articles per journal in the sample is also presented.

Although publications are spread over 29 journals, 50% are from five journals: Computers & Industrial Engineering (11.3%), International Journal of Production Research (11.3%),

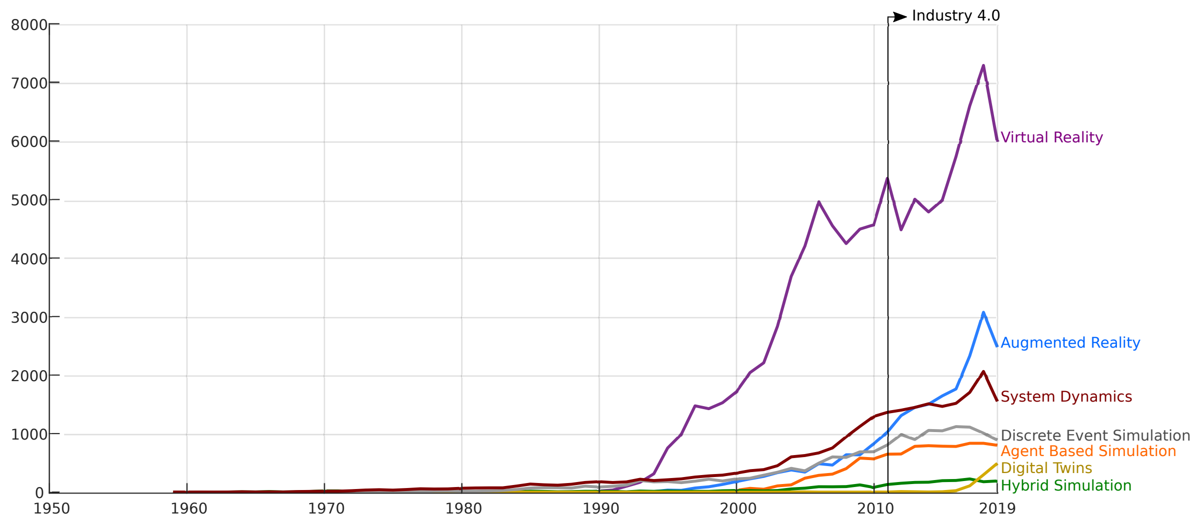

Figure 4.5 Evolution of the number of publications per simulation approach

Table 4.4 Articles by journal and period

Journal	IF	SJR	Articles published per year						Total	Percent
			14	15	16	17	18	19		
International Journal of Production Research	4.577	1.78	0	0	0	3	2	4	9	11.3%
Computers & Industrial Engineering	4.135	1.47	1	0	0	2	1	5	9	11.3%
International Journal of Computer Integrated Manufacturing	2.861	0.66	0	0	0	1	2	5	8	10.0%
Computers in Industry	3.954	1.01	0	0	1	0	2	4	7	8.8%
International Journal of Advanced Manufacturing Technology	2.633	1.00	0	0	0	1	3	3	7	8.8%
Simulation Modelling Practice and Theory	2.219	0.61	0	0	0	0	0	4	4	5.0%
Journal of Manufacturing Systems	5.105	2.11	0	1	0	1	0	1	3	3.8%
CIRP Annals-Manufacturing Technology	3.641	2.54	0	0	0	1	1	1	3	3.8%
Sustainability	2.576	0.58	0	0	0	0	0	3	3	3.8%
International Journal of Simulation Modelling	2.492	0.62	0	0	0	0	1	2	3	3.8%
IEEE Transactions on Industrial Informatics	9.112	2.35	0	0	0	0	1	1	2	2.5%
International Journal of Production Economics	5.134	2.38	0	0	0	0	0	2	2	2.5%
IEEE Access	3.745	0.78	0	0	0	2	0	0	2	2.5%
Social sciences	N/A	0.24	0	0	0	0	0	2	2	2.5%
Systems	N/A	0.40	0	0	0	2	0	0	2	2.5%
Applied Soft Computing Journal	5.472	1.41	0	0	0	0	0	1	1	1.3%
IEEE Transactions on Automation Science and Engineering	4.938	1.50	0	0	0	0	1	0	1	1.3%
Engineering with Computers	3.938	0.66	0	0	0	0	1	0	1	1.3%
Production Planning & Control	3.605	1.39	0	0	0	0	0	1	1	1.3%
Journal of Computational Design and Engineering	3.408	0.74	0	0	1	0	0	0	1	1.3%
IEEE Transactions on Human-Machine Systems	3.374	1.19	0	0	1	0	0	0	1	1.3%
Computer Networks	3.111	0.85	0	0	1	0	0	0	1	1.3%
Applied Sciences	2.474	0.42	0	0	0	0	0	1	1	1.3%
Processes	1.963	0.85	0	0	0	0	0	1	1	1.3%
Mathematics	1.747	0.24	0	0	0	0	0	1	1	1.3%
Journal of Simulation	1.214	0.87	0	0	0	1	0	0	1	1.3%
Production and Manufacturing Research	N/A	0.64	0	0	0	0	1	0	1	1.3%
Machines	N/A	0.42	0	0	0	0	0	1	1	1.3%
Organizacija	N/A	0.22	0	0	0	1	0	0	1	1.3%
		Total	1	1	4	15	16	43	80	100%

International Journal of Computer Integrated Manufacturing (10%), Computers in Industry (8.8%), and International Journal of Advanced Manufacturing Technology (8.8%). Moreover, a bibliographic coupling analysis indicates that the 80 articles in the sample are closely related, with more than 80% sharing minimum 3 and maximum 49 references. Note that "the larger the number of references two publications have in common, the stronger the bibliographic coupling relation between the publications" (Van Eck and Waltman, 2014, p. 287). The bibliographic coupling analysis and co-occurrence keyword analysis, two of the most commonly studied types of bibliometric networks (also referred to as science mapping), were carried out using VOSviewer software, highly used for visualizing bibliometric networks and text mining (Van Eck and Waltman, 2014).

To understand how the use of simulation approaches changed over time, particularly before and after the emergence of the I4.0, we observed the time series associated with the seven simulation technologies provided by the keyword analysis using Google Ngram Viewer (http://books.google.com/ngrams) and Scopus. On one side, Google Ngram is a data-mining tool based on a rich data set of words/phrases from millions of digitized books published between 1500 and 2008, widely used in data science (Skiena, 2017). On the other side, Scopus is one of the largest abstract and citation databases of scientific publications. The time series produced with Google Ngram viewer and Scopus datasets presented similar patterns up to 2008, except for Digital Twins, which Google Ngram returns no results. Fig. 4.5 shows the time series of each simulation approach based on the Scopus database. Each term was searched individually, and filtered by five subject areas closely related to the scope of this research: engineering, computer science, mathematics, decision science, and business management. Articles containing the terms in either the titles, abstracts, or keywords were retrieved.

Fig. 4.5 indicates that virtual reality, together with augmented reality, concentrates the higher number of publications. System dynamics and discrete-event simulation are the oldest methods, both with more than 50 years old. Concerning the evolution of publications, simulation-based approaches experienced a significant increase after the 1990s. However, the distribution of publications slightly changed after 2011. In the last three years, digital twin' publications increased exponentially, agent-based simulation and hybrid simulation were stable, whereas the other approaches presented a high variation.

4.4 Qualitative analysis

4.4.1 Simulation in Industry 4.0

Simulation is defined as the process of designing a model of a real or hypothetical system to describe and analyze the behaviors of the system (Scheidegger et al., 2018). The key components of this definition are: modeling – the process of creating a model; model - an abstract and simplified representation of a system, composed of a set of assumptions, which is often represented by a mathematical or logical relationship; system - the process that is analyzed; process – a collection of interrelated elements; and simulation – the operation of a model over time (Banks, 1998).

Simulation is a primary methodology for analyzing complex production systems and an essential problem-solving methodology (Negahban and Smith, 2014). A reason for using simulation are the high cost associated with the development of experiments with the actual system, to observe the behavior of processes in the real world, or with the building of a physical model (Scheidegger et al., 2018). Additionally, a model can be significantly complex to be analyzed analytically (Banks, 1998). Advantages in using simulation approaches includes: conducting tests rapidly and cheaper without disrupting the real system (risk-free environment), compressing or expanding time for a particular observation, and use of animation (visualization of dynamic systems) to facilitate communication and models validation (Banks, 1998; Borshchev, 2013; Scheidegger et al., 2018). Whereas the main disadvantages are the lack of professionals, high salaries of simulation engineers, the high cost of software licenses, and time to develop models (Banks, 1998; Kagermann et al., 2013).

There are several simulation-based approaches available in literature. Fig. 4.6 provides an overview of the simulation-based approaches being employed in the context of I4.0, based on the studies in the sample. A description of each simulation approach and an indication of key references are provided next.

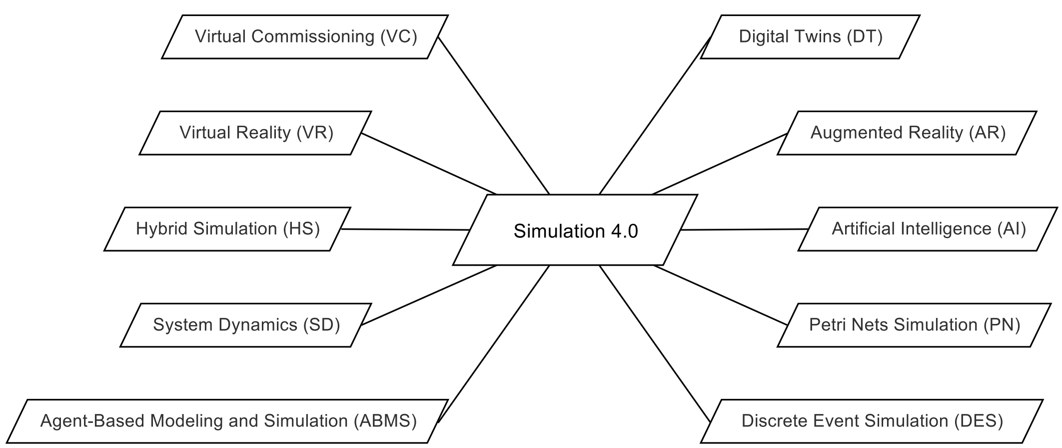

Figure 4.6 Simulation-based approaches applied in the context of Industry 4.0

Agent-based modeling and simulation (ABMS): is considered a "relatively new approach to modeling complex systems composed of interacting, autonomous agents" (Macal and North, 2010, p. 151). ABMS or Multi-Agent Systems (MAS) is also defined as "a set of elements (agents) characterized by some attributes, which interacts with each other through the definition of appropriate rules in a given environment" (Barbati et al., 2012, p. 6020). An agent is defined as a complex software unit able to operate autonomously, pursuing a set of specific goals (Frayret, 2011; Abar et al., 2017). It can represent different things, whether material or not, such as sensors, machines, products, people, and innovation (Borshchev, 2013). Generally, an ABMS model consists of a set of agents, the agents' environment, and a set of agents relationships (Macal and North, 2010). There is also a strong notion of an agent, which includes not just characteristics like autonomy, social ability, reactivity, pro-activeness, but also human-like attributes such as knowledge, belief, intention, and emotion (Wooldridge and Jennings, 1995). ABMS plays an important role in I4.0 as a modeling paradigm for CPS and simulation method (Houston et al., 2017). A review of the industrial applications of agent technology in CPS is presented in Leitão et al. (2016). A detailed software tool list for ABMS is presented in Abar et al. (2017).

Discrete Event Simulation (DES): is defined as "one in which the state variables change only at those discrete points in time at which events occur" (Banks, 1998, p. 8). The event consists of an occurrence that alters the system's state, while a state variable of a system represents all the information necessary to describe the system's behavior at a certain point in time. As an example, the number of products in a queue waiting for a quality check may be considered a state variable, and a product that is entering or leaving the queue, an event (Da Costa et al., 2017). Other key elements of DES models are passive entities (or objects), resources, locations, queues (or processing lists), source and sink blocks, and path network (Scheidegger et al., 2018). DES is process-oriented, mainly developed using process flowchart, and operates in discrete times. The abstraction level of DES models is usually medium to low. A review of DES in the scope of I4.0 is provided by Vieira et al. (2018).

System Dynamics (SD): is a continuous simulation approach to analyses dynamic systems over time, using stock and flows and feedback loops diagrams and differential equations to represent systems' components relationships (Scheidegger et al., 2018). SD has two modeling approaches (Kunc, 2017). The use of stock and flow diagrams implies a quantitative approach (hard modeling), while the qualitative approach, which is also referred to as soft operational research, involves only the use of influence (feedback loop) diagrams. SD is considered a more strategic modeling approach, where the models usually present a high abstraction level (Borshchev, 2013).

Virtual Reality (VR): is a virtual experience in which a user is immersed in a responsive virtual environment (Turner et al., 2016). It refers to a set of ICT technologies (i.e., expression technology, interaction technology, authoring technology, collaboration technology) that enables the user to experience a virtual environment in an experimental simulation (Choi et al., 2015). VR has a wide range of applications in the manufacturing industry (Berg and Vance, 2017).

Augmented Reality (AR): is a set of technologies (e.g., capturing device, visualization devices, interaction device, tracking system) that allows the direct or indirect view of the physical world environment in real-time to be augmented (i.e., enhanced) by adding virtual computer-generated devices to it (Bottani and Vignali, 2019). AR systems in manufacturing can increase a user's perception and interaction with the real world, supporting different activities such as training, assembly, and maintenance (Longo et al., 2019b; Pérez et al., 2019).

Artificial Intelligence (AI): is a domain of computer science relating to the simulation of intelligent behavior in computers. Its subfields include machine learning, deep learning, natural language processing, computer vision, cognitive computing, and more (Carvalho et al., 2019; Lolli et al., 2018). AI can also be described as a set of techniques for modeling and simulation of environmental systems, which includes artificial neural networks, fuzzy models, reinforcement learning, cellular automata, and meta-heuristics (Chen et al., 2008).

Petri Nets simulation (PN): is a discrete-event graphical and analytical tool used to model and simulate flexible manufacturing systems (Başak and Albayrak, 2014; Pisching et al., 2018). In other words, PN formalism is suitable for representing concurrent, asynchronous, distributed, parallel, and stochastic systems (Guo et al., 2017; Drakaki and Tzionas, 2015). There are different extensions to PN. Overall, a PN consists of four elements: places - represented by circles, transitions - represented by rectangles, edges - represented by direct arrows, and tokens - represented by small solids (Pisching et al., 2018).

Hybrid Simulation (HS): is characterized by the combination of two or more simulation methods, i.e., multi-paradigm model (Scheidegger et al., 2018; Brailsford et al., 2019) or combination of simulation with optimization approaches, i.e., simulation-optimization (de Sousa Junior et al., 2019). The introductory guide for HS presented in Scheidegger et al. (2018) compares in detail the three of the main simulation methods in industrial engineering, i.e., DES, ABMS, and SD. Another key reference on HS is the literature review conducted by Brailsford et al. (2019), which also presents a conceptual framework to guide the development of HS projects. According to the authors, there are four types of hybridization: sequential - the output of one model is the input to another model; enriching – narrow use of another method by one dominant; interaction – the models interact cyclically without dominance; and integration – where it is not easy to distinguish the beginning of one method and the ending of another method. They also provide guidelines to combine simulation methods with optimization approaches (e.g., exact or heuristic methods). There are different kinds of HS models in the literature, such as DES-ABMS (Farsi et al., 2019), SD-ABMS (Nassehi and Colledani, 2018), DES-VR (Turner et al., 2016), ABMS-Data Science (Houston et al., 2017), Simulation-Big data (Vieira et al., 2019b), PN-AI (Drakaki and Tzionas, 2017), and multi-level simulation (Delbrügger et al., 2019). Most authors employ the term HS to describe their models, even though the taxonomy for classifying simulations with multiple models proposed by Lynch and Diallo (2016) may be considered in future research.

Digital Twins (DT): refers to the digital representation of a physical system and the seamless integration between the physical and digital spaces (Cimino et al., 2019). DT is commonly defined as "a multi-physics, multi-scale, probabilistic, ultra-fidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on historical data, real-time sensor data, and physical model" (Tao et al., 2018b, p. 2406). It was initially developed within the aerospace industry than extended to the manufacturing field (Rodič, 2017; Tao et al., 2018b). Essentially, DT is a hybrid approach, built into four levels: geometry, physics, behavior, and rule (Tao and Zhang, 2017). The first two levels involve mainly kinematics and geometric simulation, also referred to as continuous simulation (Klingstam and Gullander, 1999), which is based on computer-aided technologies, such as computer-aided design (CAD), computer-aided engineering, and computer-aided manufacturing as well as finite element analysis (Dankwort et al., 2004). Levels three and four involve different simulation approaches, such as DES, ABMS, and AI techniques (Schluse et al., 2018). Tao and Zhang (2017) and Tao et al. (2018b) review the role of DT in the manufacturing industry. A review of the influence of I4.0 on the development of DT is presented in Rodič (2017).

Virtual Commissioning (VC): is a digitalization method to speed up the commissioning of a new production process through a virtual environment (Lechler et al., 2019). It is a testing method that makes use of simulation models and emulated controllers during the development and validation of new manufacturing systems (Ahrens et al., 2018). VC integrates different technologies, such as 3D CAD, DES, and PLC. DT models have also been incorporated into the process of virtual commissioning. DT models, along with PCL design, give an even more accurate view of how automated systems design will perform prior to physical commissioning when hardware and PLCs are put together. A brief review of VC can be found at Lechler et al. (2019) and Putman et al. (2017).

4.4.2 Industry 4.0 design principles

Defining constructs clearly, in a desegregate approach, is essential to advance scientific research in the intersection of I4.0 and simulation fields, because it aids identifying variables and operational definitions for modeling, simulation and the development of theories (Davis et al., 2007; Harrison et al., 2007). It is important to support companies in identifying and implementing I4.0 projects (Hermann et al., 2015). Although there is no consensus on the definition of I4.0, some of its core technological components and design principles can be identified and used to support the implementation of I4.0 scenarios in companies (Hermann et al., 2015, 2016), and model and simulate those scenarios in a risk-free virtual environment prior to real implementation. Similar strategies have been used to characterize other important managerial approaches, such as Lean Production. In summary, I4.0 design principles are fundamental concepts that describe the I4.0 phenomenon and support its implementation (Ustundag and Cevikcan, 2017).

Ten articles describing the I4.0 design principles were selected for analysis, following the search protocol and eligibility criteria described in Section 4.2.2 (Kagermann et al., 2013; Lasi et al., 2014; Hermann et al., 2015, 2016; Ustundag and Cevikcan, 2017; Ghobakhloo, 2018; Mabkhot et al., 2018; Mittal et al., 2018; Ruppert et al., 2018; Tavcar and Horvath, 2019). Fig. 4.7 and Table 4.5 provides an overview of the 17 design principles of I4.0 identified from these articles, extending the list provided by Ghobakhloo (2018).

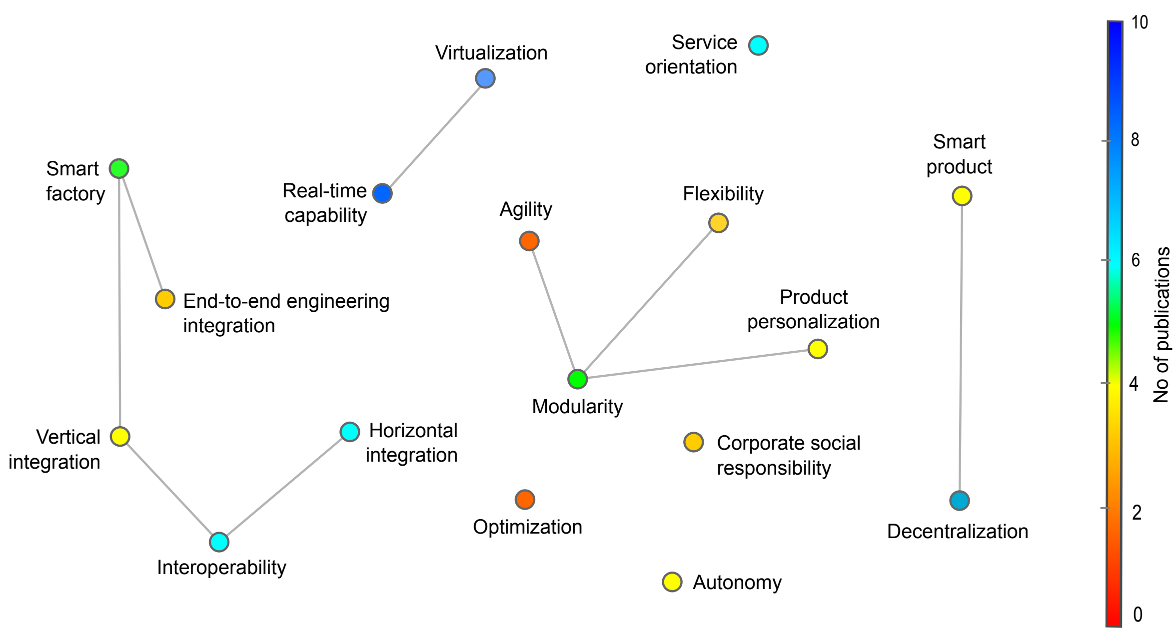

Figure 4.7 Design principles of Industry 4.0.

Legend: Each node represents a principle. The color of the node indicates the number of articles in the sample. The edge (line) represents a key relationship between principles.

Table 4.5 Description of Industry 4.0 design principles

Principle	Description
Vertical integration:	is the integration of different ICT systems within a company at the different hierarchical levels, i.e., physical, software application, business processes (Kagermann et al., 2013). It refers to intra-company integration and networked manufacturing systems (Alcácer and Cruz-Machado, 2019), following a bottom-up automation pyramid approach, which is mostly described in terms of five levels: 1 - field level (devices, sensors and actuators); 2 - control levels (programmable logic controllers - PLC); 3 - supervisory level; 4 - planning level; and 5 - management level (Snatkin et al., 2013; Schlechtendahl et al., 2014; Wang et al., 2016a).
Horizontal integration:	consists of inter-company integration of IT systems (Alcácer and Cruz-Machado, 2019), both within and across an organization (Kagermann et al., 2013), enabling collaborative networks of companies share resources, capabilities, and information in real-time across the value chain (Brettel et al., 2014).
End-to-end engineering integration:	it refers to the digital integration of system engineering across the entire value chain, including product design and development, production planning, production engineering, production, and services (Kagermann et al., 2013; Wang et al., 2016a). It implies a holistic system engineering approach and digital product life-cycle management, encompassing both the production process and the manufactured product (Kagermann et al., 2013; Tao et al., 2018a).
Smart factory:	refers to extensively integrated and collaborative manufacturing systems, which are capable of responding in real-time to changes in demands and conditions in the factory (Mabkhot et al., 2018). It consists of a network of smart objects or interconnected cyber-physical systems, and its main features include comprehensive connection, deep convergence, and reliance on data-driven simulation-optimization (Wang et al., 2016a,b; Kusiak, 2018).
Interoperability:	indicates the capacity of two or more systems to coexist, interact (exchange information), and interoperate, i.e., share resources (Gorkhali and Xu, 2016; Schlechtendahl et al., 2014). It refers to the ability of CPS components and IT systems having different standards to connect and communicate with each other (Mabkhot et al., 2018).
Modularity:	is an engineering concept that refers to the degree in which a product or system can be decomposed in re-combinable modules (Mabkhot et al., 2018) that are units “composed of a set of components with a set of specific interfaces” (Efatmaneshnik et al., 2018, p. 365). Modularity applies to the different stages of the production cycle (e.g., design, fabrication, assembly), enabling mass customization, and flexible and agile manufacturing systems (Hermann et al., 2015; Mabkhot et al., 2018; Efatmaneshnik et al., 2018; Ghobakhloo, 2018).
Real-time capability:	refers to data collection and analysis in real-time to support data-driven decision making (Tavcar and Horvath, 2019). It can be subdivided into three categories: real-time monitoring, real-time data analysis, and real-time decision-making (Mabkhot et al., 2018). The main technological enablers for real-time systems capabilities are industrial automation, IoT, CPS, cloud computing, big data, and simulation (Kagermann et al., 2013).
Virtualization:	refers to the virtual replication of a physical system by linking sensors and actuators data with digitized factory model (Hermann et al., 2016), in which a virtual system can be used to monitor, simulate and control its physical counterpart (Mabkhot et al., 2018). Virtualization is mainly related information transparency and to enabling technologies such as CPS, virtual reality, augmented reality, digital twin, and virtual commissioning (Hermann et al., 2015; Ghobakhloo, 2018; Mabkhot et al., 2018).

Continued on next page

Table 4.5 – *Continued from previous page*

Principle	Description
Decentralization:	means that the system network, where the decision is made, is not centrally controlled. It is directly related to the idea of self-organization and emergent behaviors, where lower-level components act on local information to achieve global goals (Kamdar et al., 2018; Oh et al., 2015; Tang et al., 2018).
Autonomy:	generally means that a system can operate and make decisions autonomously, without external instructions or intervention (Kamdar et al., 2018). It also suggests self-learning capabilities, i.e., the ability of a system to learn and adapt (Tavcar and Horvath, 2019). Autonomy equips a production system with the capacity to respond to unforeseen events intelligently (Kagermann et al., 2013). However, a system may have different degrees of autonomy (Santa-Eulalia et al., 2012; Tavcar and Horvath, 2019).
Optimization:	is related to resource productivity and efficiency (Kagermann et al., 2013). It usually refers to prescriptive models used to find an optimum or near-optimum solution for a problem described in terms of a function and a set of constraints, ensuring the higher performance of a system, e.g., operational, economic, and environmental performance (de Souza Dutra et al., 2020). It "consists of searching the best solution, according to a given criterion, among a set of feasible solutions" (Barbati et al., 2012, p. 6021). It is also related to self-adjust and self-optimize functions (Ruppert et al., 2018; Tavcar and Horvath, 2019).
Flexibility:	refers to the ability of manufacturing systems and supply chains network to adapt and respond (proactively or reactively) to turbulent demand and changing environments (Lasi et al., 2014; Yu et al., 2015).
Agility:	is mainly related to responsiveness and speed to respond to changes. It is the capability of systems to be agile and to respond to unexpected or unplanned events quickly (Tukamuhabwa et al., 2015). It is characterized by visibility, short lead times, and rapid detection and reaction (Giannakis and Louis, 2016).
Service orientation:	refer to new business models, such as factory as a service (FaaS), were organizations shift the focuses of obtaining profit from selling products to selling services (Mabkhot et al., 2018). "In this environment, complex manufacturing tasks can be accomplished collaboratively by several manufacturing services from different companies" (Ghobakhloo, 2018, p. 922).
Smart product:	refers to uniquely identifiable and all times located products that carry information about itself, about its environment, and its users (Kagermann et al., 2013; Mabkhot et al., 2018). Smart products are also referred to sensor-embedded products, and can be implemented through RFID tags, which allow storing and transmitting all information required for its production to machines (Hermann et al., 2015; Li et al., 2017a).
Product personalization:	refers to production based on customized orders (lot size-1), where buyers dictate the conditions of the trade (Lasi et al., 2014). Product personalization also means that customer-specific criteria can be incorporated into the different phases of product development and that later modification in orders can be easily managed (Kagermann et al., 2013).
Corporate and social responsibility:	refers to environmental sustainability, resource efficiency, and labor regulations (Lasi et al., 2014; Ruppert et al., 2018). I4.0 will create new social infrastructures in the workplace, affecting job creation, competence profiles, training strategies, and increasing the participation of workers in the innovation process (Kagermann et al., 2013). Moreover, I4.0 emphasizes that sustainability, resource productivity and efficiency should be at the center of the design and operations of industrial manufacturing processes (Lasi et al., 2014).

A seminal reference in I4.0 is the final report of the *Industrie 4.0* working group (Kagermann et al., 2013), which initially described its vision, potential, research requirements, and priorities for further research. From this report, the essential building blocks of I4.0 are vertical integration, smart factories, horizontal integration, and end-to-end digital integration of engineering. Additionally, Lasi et al. (2014) indicates flexibility, product personalization, decentralization, virtualization, and corporate social responsibility as main drivers and fundamental concepts of I4.0. Hermann et al. (2015) systematically reviewed the critical features of I4.0, identifying six design principles for I4.0 implementation: modularity, interoperability, real-time capability, virtualization, decentralization, and service orientation. These six principles were also analyzed in Mabkhot et al. (2018) and Ruppert et al. (2018). An aggregate analysis is presented in Hermann et al. (2016), which describes four I4.0 design principles (i.e., interconnection, technical assistance, decentralized decisions, and information transparency). Other key feature that characterizes the I4.0 includes autonomy, smart product, optimization, and agility (Ustundag and Cevikcan, 2017; Mittal et al., 2018; Tavcar and Horvath, 2019).

Key relationships between I4.0 design principles

All I4.0 design principles are related to some extent. Although it is beyond the scope of this study to analyze all relationships and or dependencies between principles, it is important to highlight some key relationships described in the analyzed papers, represented by the arcs in Fig. 4.7. They are:

- Interoperability enables vertical and horizontal integration (Burke, 2017; Mabkhot et al., 2018).
- Modularity enables flexibility, agility, and product personalization (Hermann et al., 2015; Mabkhot et al., 2018; Efatmaneshnik et al., 2018; Ghobakhloo, 2018).
- Vertical integration enables smart factory (Ustundag and Cevikcan, 2017; Tavcar and Horvath, 2019).
- Smart manufacturing enables digital end-to-end engineering (Kagermann et al., 2013).
- Virtualization of production systems depends on real-time capabilities (Hermann et al., 2015; Ghobakhloo, 2018).
- Decentralization can be achieved through smart products (Kagermann et al., 2013; Hermann et al., 2015, 2016).

There are different levels of interoperability (i.e., technical, syntactic, semantic, organizational) and interoperability technologies, such as AutomationML (Automation Markup Language) and OPC UA (Open Platform Communications Unified Architecture), which are part of the reference architecture model for Industrie 4.0 (RAMI4.0) (Mabkhot et al., 2018; Ghobakhloo, 2018). These technologies enable vertical and horizontal integration by providing semantic interoperability for connected systems, allowing multi-vendor heterogeneous devices, machines, processes, and systems to communicate and information to flow seamlessly from field level to business level (Burke, 2017; Mabkhot et al., 2018).

Modularity allows achieving product personalization through combination, modification, or addition of modules, in a modular design of products (Duray et al., 2000; Efatmaneshnik et al., 2018; Ghobakhloo, 2018). Modularity also enables increased flexibility and agility of production systems to respond to fluctuating demands by reducing lead-time through a fast (plug & play) combination of modules with compatible software and hardware interfaces (Hermann et al., 2015; Li et al., 2019), wherein functionalities can be added or removed more quickly from a system (Efatmaneshnik et al., 2018; Mabkhot et al., 2018), as in modular and reconfigurable manufacturing systems (Kim et al., 2020).

The vertical integration of hierarchical subsystems serves as a backbone for implementing the smart factory, by connecting sensors and actuators in the field level up to management level (Wang et al., 2016b; Ustundag and Cevikcan, 2017; Tavcar and Horvath, 2019), which in turn supports end-to-end digital integration by allowing vertical networking of smart production systems (Kagermann et al., 2013; Wang et al., 2016a) endowed with reasoning, learning, adapting, and evolving capabilities (Tavcar and Horvath, 2019), which is crucial to support mass product personalization (Wang et al., 2016a).

Virtualization suggests that cyber-physical systems can monitor physical processes, which rely on real-time capabilities, such as real-time data collection (Ghobakhloo, 2018). It is associated with digital twins, wherein "sensor data are linked to virtual plant models and simulation models" (Hermann et al., 2015, p. 15) to monitor, analyze and optimize the physical process in real-time (Mabkhot et al., 2018; Tao et al., 2018b).

Decentralization can be achieved through smart products due to smart products' capability to store and exchange data with smart processes throughout its lifetime and to actively control the manufacturing process (Kagermann et al., 2013; Kagermann, 2015; Hermann et al., 2015; Alqahtani et al., 2019). Decentralized controlled production systems based on smart products can produce by following the specifications and instructions recorded in an RFID tag embedded or attached to the product or product carrier (Kagermann et al., 2013; Wang et al., 2016b; Li et al., 2017a; Mabkhot et al., 2018).

4.4.3 Linking simulation approaches with Industry 4.0 design principles

After identifying the simulation-based approaches used relative to I4.0 and the design principles of I4.0, we proceeded with the cross-analysis of the concepts. To understand the I4.0 design principles that are captured by each simulation-based approach, we assessed all studies in the sample (see Appendix A). Initially, the articles were grouped by the simulation approaches used. Thereafter, key terms (i.e., I4.0 design principles) were searched in the text. Subsequently, the context wherein the string is invoked was analyzed to identify any explicit relationship between the simulation approach and the I4.0 design principle established by the authors. Thereafter, full-text articles were assessed relative to model conception, implementation, and analysis to identify implicit relationships. To increase the validity and reliability of the analysis, a triangulation by investigators (Bengtsson, 2016) was performed. Two investigators performed the analysis separately and thereafter, discussed their results at weekly meeting to obtain consensus. If no consensus was reached, a third investigator was consulted to reach the final decision. Tab. 4.6 summarizes the main relationships between simulation approaches and I4.0 design principles, from the authors' perspective, where the symbols mean that the I4.0 design principle is captured (●), partially captured (◑), or non-captured by a simulation approach (○).

Table 4.6 Linking simulation-based approaches with Industry 4.0 principles

Approach	I4.0 design principle																
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17
ABMS	●	◑	○	◑	●	●	●	◑	●	●	●	●	●	◑	◑	◑	◑
DES	○	◑	○	○	○	○	◑	◑	○	○	●	●	●	●	○	○	◑
SD	○	◑	○	○	○	○	◑	◑	○	○	●	●	○	◑	○	◑	○
VR	◑	○	○	◑	○	○	●	●	○	○	●	●	○	●	●	●	◑
AR	○	○	○	◑	●	○	●	●	◑	○	●	●	◑	●	●	◑	○
VC	●	◑	◑	◑	◑	◑	◑	◑	○	○	●	●	◑	●	◑	◑	○
PN	●	◑	○	◑	◑	◑	◑	◑	○	○	●	●	◑	○	○	◑	○
AI	◑	○	○	●	◑	◑	●	●	●	●	●	●	◑	●	●	◑	○
DT	●	●	◑	●	●	●	●	●	◑	◑	●	●	◑	●	◑	◑	◑
HS	●	●	◑	●	●	◑	●	●	●	●	●	●	●	●	◑	◑	◑

The symbols mean I4.0 design principle captured (●), partially captured (◑), or non-captured (○) by the simulation approach. The abbreviations are: P1 - Vertical integration; P2 - Horizontal integration; P3 - End-to-end engineering integration; P4 - Smart factory; P5 - Interoperability; P6 - Modularity; P7 - Real-time capability; P8 - Virtualization; P9 - Decentralization; P10 - Autonomy; P11 - Optimization; P12 - Flexibility; P13 - Agility; P14 - Service orientation; P15 - Smart product; P16 - Product personalization; P17 - Corporate and social responsibility; ABMS - Agent Based Modeling and Simulation; DES - Discrete Event Simulation; SD - System Dynamics; VR - Virtual Reality; AR - Augmented Reality; VC - Virtual Commissioning; PN - Petri Nets; AI - Artificial Intelligence; DT - Digital Twins; HS - Hybrid Simulation.

Vertical integration (P1) and horizontal integration (P2) can be modeled using ABMS (Wang et al., 2016b) or PN formalism (Haag and Simon, 2019; Pisching et al., 2018; Guo et al., 2017). Other approaches, such as VR, DT, and VC, also depicts these principles. The DT-based model proposed by Zhang et al. (2017), Zhou et al. (2019), and Schluse et al. (2018) integrates intra-company level data from sources, such as human workers, sensors/actuators, manufacturing execution systems, and kinematics/dynamics. At inter-company level, Vieira et al. (2019a) and Vieira et al. (2019b) proposed a decision support system that integrates different supply chain' data sources and reproduces material and information flow using a hybrid data-driven simulation model, allowing supply chain disruption scenarios to be evaluated.

DT together with VR are two promising technologies to deploy end-to-end engineering integration (P3) across a value chain, by allowing the combination of a physical entity with a high-fidelity virtual counterpart and creation of immersive virtual environments. The potential application of DT throughout the product-life-cycle is indicated in several studies (Tao and Zhang, 2017; Rodič, 2017; Tao et al., 2018b; Cimino et al., 2019). However, there are several challenges to be addressed to make it feasible, as listed in Tao et al. (2018a). However, some studies proposed addressing these principles partially. Sierla et al. (2018) combines DT with product-centric control, wherein the virtual counterpart of a product (developed from the virtual product description) inquires its own manufacturing services, allowing potential manufacturing suppliers to be involved in the product design phase and assembly planning. The authors present two example cases as a proof-of-concept. Cecil et al. (2019) proposed an IoT-based CPS framework, wherein a VR-based collaborative environment is used to support distributed micro-devices assembly planning. The authors developed a testbed to demonstrate the feasibility of their approach.

A smart factory (P4) is often modeled as a multi-agent system. Wang et al. (2016b) proposed a smart factory framework, modeling physical resources as different types of agents, forming a self-organized MAS system with feedback and coordination based on Big Data. Nagadi et al. (2018) presented a framework for smart factory assessment using ABMS to determine a machines' behaviors and DES to mimic process flows.

The principles interoperability (P5) is explored by different approaches, such as ABMS, HS, DT, and VC models. Laurindo et al. (2019) proposed an integration mechanism for HS or VC approach, by allowing online communication and high-level data exchange between DES and the dynamic system simulation software. From the authors, the integration between the DES model and the control system enables the validation of PLC logic and other different operational aspects of a production system. Vieira et al. (2020) presented a simulation-based approach to address problems related to the integration of big data, from different data sources, into supply chain simulation models. Schluse et al. (2018) introduced the concept of experimentable digital twins that combines DT with model based systems engineering and simulation technology, wherein its components communicate through a simulated communication infrastructure, mirroring the real communication infrastructure of its physical counterparts. A general approach to transform legacy systems into Industry 4.0-ready by connecting production systems with different interfaces is presented in Schlechtendahl et al. (2014).

Modularity (P6) links to the strategy of modular simulation, used to reduce the model building complexity, and to the capacity to reuse and share sub-models (Delbrügger et al., 2019). It is an important feature of agent systems (Heydari and Dalili, 2015; Rodrigues et al., 2018). Farsi et al. (2019) proposed a modular HS framework, combining DES with ABMS for a modular manufacturing system design, which considers different abstraction levels. Zhang et al. (2017) uses 3D reference models and modular encapsulation to aid individualized designs and virtual assembly. Zhou et al. (2019) and Delbrügger et al. (2019) integrated several simulation modules. To achieve modularity, Tan et al. (2019b) proposed the smart assembly units, which encapsulate assembly functions and data-drive capabilities, enabling decomposition and reconfiguration of assembly processes, implemented in an event-driven multi-agent reinforcement learning approach.

Real-time capability (P7) and Virtualization (P8) are mainly related to the capacity to collect and integrate CPS/ IoT-data (or big data) into the simulation models. Saez et al. (2018) used an HS approach to assess the performance of production systems in real-time, monitoring and analyzing machines' continuous and discrete variables in virtual environments operating synchronously to factory floor equipment. Turker et al. (2019) present a decision support system for dynamic job-shop scheduling that collects data from an IoT system and act on jobs processing orders, testing the system under different demand scenarios through a DES model. Houston et al. (2017) combined ABMS with data science to evaluate the return on investment of installing an IoT system, used to collect continuous real-time data in support of predictive maintenance. A multi-view of a DT real-time data synchronization logic to link a physical system with and virtual simulation model is described in Zhang et al. (2017).

Decentralization (P9) is captured through an ABMS, which enables distributed decision making at different levels, i.e., machine level, system level, or to create collaborative enterprise networks. Kaihara et al. (2017) proposed a simulation model to evaluate the effectiveness of crowdsourced manufacturing using ABMS and DES, wherein business entities share their manufacturing resources based on their demand and available capacity. A continuation of this study is presented in Kádár et al. (2018), wherein the authors propose a bi-level simulation model to support asset sharing in a large federated network of manufacturers. In their model, each factory agent integrates a DES model and has an interface to communicate with an agent-based collaboration platform, which establishes the negotiation mechanism. Similarly, a distributed approach based on ABMS and DES for multi-machine preventive maintenance scheduling is proposed in Upasani et al. (2017). Other examples include the VR-based simulation approach for evaluation and validation of manufacturing assembly planning from distributed locations, proposed by Cecil et al. (2019), and a DT-based distributed approach is presented in Liu et al. (2018).

Autonomy (P10) is determined by agent design (i.e., ABMS), wherein system entities are modeled as autonomous intelligent agents. The intelligence of the agent is usually modeled in terms of "if-else" statements, optimization methods, or following an AI technique. UML statechart and sequence diagram are employed as a conceptual modeling tool to describe the behaviors and communications between agents. An ABMS with reinforcement learning for intelligent planning and scheduling is described in Tan et al. (2019b). Grundstein et al. (2017) proposed an autonomous production control method for complex job shop manufacturing using heterarchical structures, validated through a DES model. Other examples of simulation models with intelligent mechanisms can be found in Ghadimi et al. (2019) and Carvajal-Soto et al. (2019).

All ten simulation-based approaches can capture optimization (P11) and flexibility (P12) principles by adjusting the parameters in the models in multiple evaluation scenarios or by incorporating mathematical optimization approaches into the models. Trebuna et al. (2019) combined the value stream mapping (VSM), a Lean manufacturing tool, with a DES model to identify improvement opportunities that optimize production flows and increases the flexibility and productivity of a production system. Frazzon et al. (2018) proposed an HS model to optimize production scheduling and transport planning in supply chains by combining a mixed-integer programming model, a DES model, and a genetic algorithm iteratively. Zhang et al. (2017) describes how DT models can perform real-time optimization of production systems. In addition, Zhou et al. (2019) proposed a knowledge-driven DT framework that enables self-optimizing manufacturing systems. Human-robot collaboration in the physical and virtual space is another promising technology of I4.0 to improve manufacturing flexibility. In this regard, Pérez et al. (2019) presented a VR-based framework to support training, simulation, and VR-operated robotic systems through an immersive virtual environment.

Simulation models capture agility (P13) in approaches such as, by supporting multiple scenarios evaluations, distributed collaboration and by increasing information transparency. Schönemann et al. (2015) proposed an HS model, that combines DES with ABMS, to evaluate the development of agile manufacturing systems based on redundant job shop work stations and flexible product routing. In Vieira et al. (2019a), disruptive events were triggered in different geographic locations in supply chain simulation run time to analyze system' performance impact related to terms of stock levels and unfilled orders. To address the need for agile manufacturing, Sierla et al. (2018) combined DT with product-centric control, proposing a framework to aid collaborative product design and factory planning.

Service orientation (P14) can be achieved through data-driven simulation, wherein users can develop and run simulation models with minimum or no knowledge in programming, in a self-contained service. This enhances the model maintainability, reusability, and ability to support decision making in complex systems (Guizzi et al., 2019). An example is presented in Goodall et al. (2019), which proposed a data-driven simulation approach for remanufacturing operations using DES and object-oriented programming paradigm. Their simulation model predicts material flow in a generic and reusable manner, reflecting changes in real systems without manually change the simulation construct. Moreover, the concept of software as a service (SaaS) is applied in Kádár et al. (2018).

Smart product (P15) enables data-driven simulation approaches. Alqahtani et al. (2019) developed a DES model to predict an optimal warranty policy for remanufactured products and components, wherein an end-of-life product is equipped with RFID sensors to collect and transfer critical product pieces of information. Furthermore, modeling as an agent system, Benotsmane et al. (2019) and Benotsmane et al. (2019), described a model that considers iterative smart working pieces.

Product personalization (P16) also implies smart production lines. Zhang et al. (2017) and Zhang et al. (2017) proposed a DT-driven platform for rapid individualized designing of production systems, which combines a reference model, distributed simulation, and multi-objective optimization models to support the quality of design and quality of conformance. From Park et al. (2019), a mean to achieve customization/personalization is operating factory as a service (FaaS) in a distributed manufacturing system. To achieve this, they proposed a DT-based approach. Tamás (2017) proposed a DES model to improve the performance of intermittent production systems, to enable managing several product variants, in a customer-oriented approach.

Corporate and social responsibility (P17) can be analyzed in terms of impact analysis and resource efficiency. Ghadimi et al. (2019) proposed a framework for sustainable supplier evaluation and selection in the I4.0 supply chain using agent technology. Charnley et al. (2019) explored the relationship between circular economy and I4.0 through an HS approach, combining a DES and an SD model to enable a data-driven circular economy, focusing on remanufacturing processes in the automotive industry. Yazdi and Azizi (2019) considered the concept of manufacturing sustainability, thus, proposed a DES model to evaluate an improvement project before implementation, showing an impact on production systems' operational performance and energy consumption. Longo et al. (2019b) proposed a VR-based system for emergency response training in industrial sites, applicable to emergency management and disaster/risk preparedness enhancement, as well as to support companies comply with security norms and reduce environmental risks.

4.4.4 Classification scheme and assessment

To aid further content analysis, and assess central aspects of the studies employing a simulation-based approach in I4.0, a classification scheme with five categories, subdivided into 61 subcategories was proposed (see Fig. 4.8). The dataset used to display the results in Fig. 4.8 is available in the Appendix A.

The first category represents the simulation-based approaches identified through quantitative and qualitative analysis, as described previously. The second category, adapted from Jahangirian et al. (2010), is used to assess the empirical nature of the studies. Here, real problem solving (RPS) refers to models that use real data gathered from real processes to solve a real problem. In contrast, hypothetical problem solving (HPS) uses artificial data (e.g., randomly generated instances) to solve a real-life problem. The RPS has a stronger internal validity compared to HPS, which subsequently presents a stronger external validity, focusing on providing solutions that can be generalized.

The third category, adapted from Harrison et al. (2007), classifies the purpose (or use) of simulation models into seven categories: (1) prediction – analysis of variables relationships through simulation output, which can also be seen as hypotheses subject to empirical testing; (2) proof – relates to resulting system behavior, used to show that the system modeled can yield specific types of behaviors; (3) discovery – identification of unexpected behaviors through system entities interaction analysis; (4) exploration – analysis of the conditions wherein a particular behavior is produced; (5) critique – examination of a pre-existing theoretical explanation for a phenomenon; (6) prescription - recommendations to improve operations effectiveness; (7) empirical guidance – support the development of new theories and empirical research.

Category four, adopted from Harrison et al. (2007) and Jahangirian et al. (2010), is used to classify the studies per area of application related to the field of industrial engineering. The fifth category groups the design principles of I4.0 identified through the qualitative analysis of studies included in phase 2 of the systematic review. The key results from the content analysis were thereafter computed using the defined classification scheme, summarized in

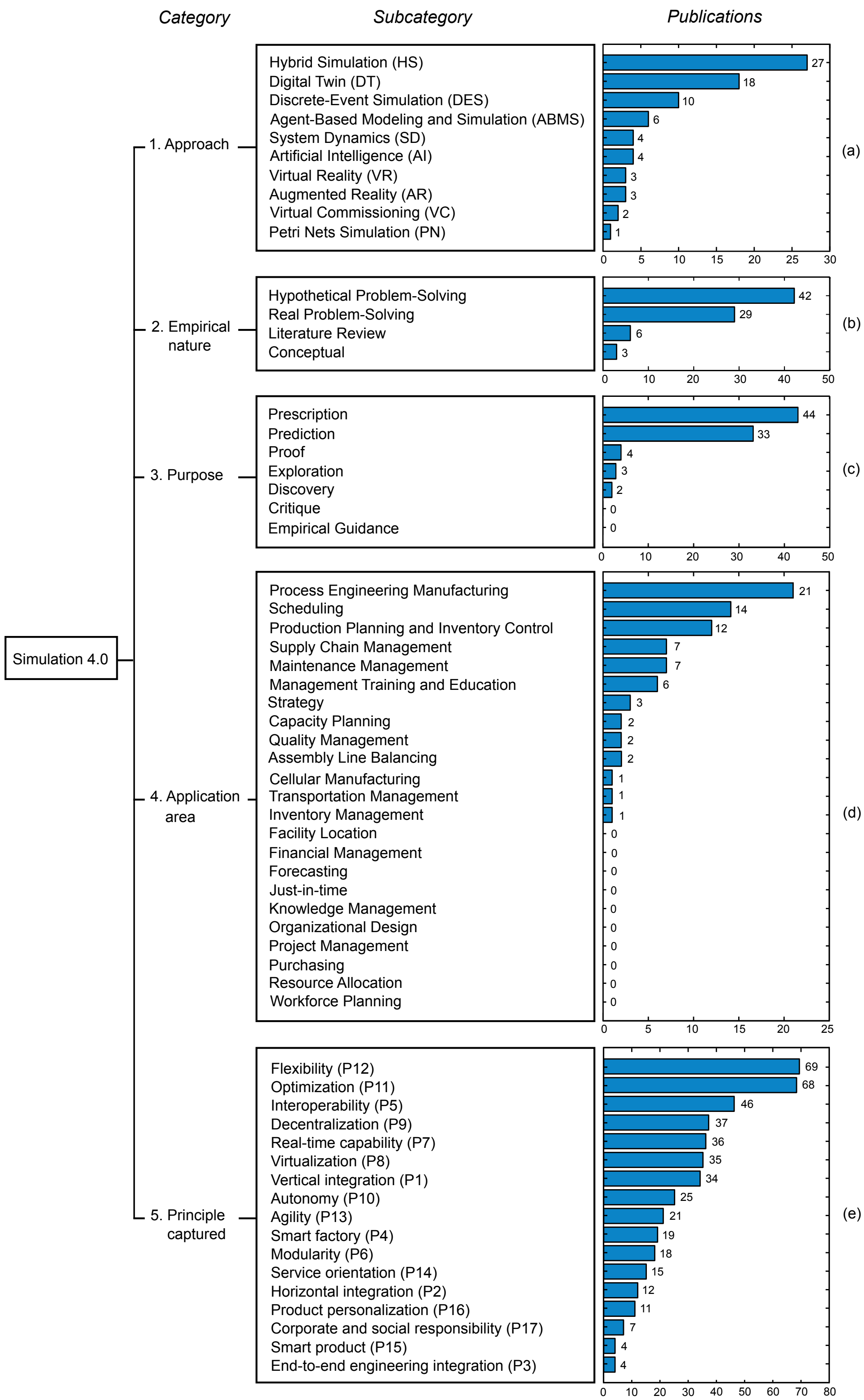

Figure 4.8 Classification scheme and assessment results

Fig. 4.8, where each publication can be classified into no, one, or multiple categories.

Overall, 10 simulation-based approaches and 17 design principles of I4.0 were identified. The more significant part of the simulation-based studies (over 55%) employs hybrid simulation or digital twin (see Fig. 4.8a). DES and ABMS also play a vital role in I4.0, being applied in 20% of the sample. In addition to that, most HS models integrate DES and/or ABMS approach. Other approaches are represented in the sample as follows: SD (4 articles, 5%); AI techniques (4 articles, 5%); VR (3 articles, 3.8%); AR (3 articles, 3.8%); PN (1 article, 1.3%). As concerns model implementation, the studies use very different software tools. Of these, the most frequent are AnyLogic (8 articles, 10%), Arena (7 articles, 8.8%), Tecnomatix plant simulation (6 articles, 7.5%), and MATLAB/Simulink (5 articles, 6.3%). In terms of programming languages, Java stands out with 19 articles, representing 23.8% of the sample size. Furthermore, AnyLogic is also based on Java programming.

For the empirical nature (see Fig. 4.8b), the majority of these studies (42 articles, 52.5%) used artificial data based on hypothetical cases or randomly generated instances. In contrast, 29 studies (36.3%) used real-data. Additionally, 6 review articles (7.5%) and 3 theoretical-conceptual articles (3.8%) were identified. In general, the review articles focused on a specific simulation method. Rodič (2017), Tao et al. (2018b) and Cimino et al. (2019) focus on DT. Vieira et al. (2018) center on DES, and Turner et al. (2016) on DES-VR. Mourtzis (2019) emphasizes the historical evolution of simulation technologies. They all have a different scope and design compared to this research. For applications (see Fig. 4.8d), most of the studies (57.5%) focused on process engineering manufacturing, scheduling, or production planning and inventory control. Together, supply chain management, maintenance, education/training represents 25% of the sample. Nevertheless, 10 out of 23 areas related to the field of industrial engineering are unexplored. Lastly, Fig. 4.8e shows that all 17 design principles of I4.0 identified can be captured by simulation technology. However, the extensiveness wherein the design principles are captured varies depending on the simulation approach. HS and DT consider a higher number of I4.0 principles. End-to-end engineering integration, smart product, and corporate social responsibility are the principles least addressed by these studies.

4.5 Discussion

This review's results reveal an increasing trend in the number of publications on simulation in I4.0 in the last 4 years. This result reinforces the importance and potentials of simulation technologies to support the implementation of I4.0, as indicated by other academics, industry experts, and leading simulation software vendors (Kagermann et al., 2013; Shih, 2016; Thilmany, 2017; Tao et al., 2018a; Lugert et al., 2018; Jeong et al., 2018; Han et al., 2018;

AnyLogic, 2020; Ghobakhloo, 2018; Martin, 2019). It is consistent with the recommendations in the final report from the German *Industrie* 4.0 working group to develop the I4.0, which is a primary reference on I4.0. It is also consistent with the findings of the empirical research conducted by Lugert et al. (2018) with 170 industry experts, which reveals simulation as an essential technique to enhance continuous improvement tools to plan and guide companies' transition to I4.0. Moreover, the use of simulation technologies is incorporated as part of industry leaders' strategy (e.g., General Electric, Siemens, Bosch, Airbus) on the path to I4.0 digital transformation (Tao et al., 2018b; AnyLogic, 2020; Vieira et al., 2019b,a; Deloitte, 2018). Furthermore, from the ABI research group, I4.0 stimulates investments (in billions of dollars) in plant simulation software (Martin, 2019). The global survey conducted by Deloitte (2018) with 361 executives about I4.0 also indicates companies' investments to adopt advanced simulation and modeling technologies to access, analyze and leverage data from assets. We can therefore infer that the research area at the intersection of I4.0 and simulation fields will continue to grow in the coming years owing to its relevance to industry.

4.5.1 RQ1 – What are the simulation-based approaches being employed in the context of I4.0?

In addressing the first research question, 10 simulation-based approaches are used in the context of I4.0: DES, SD, ABMS, HS, PN, AI, VR, AR, VC, and DT. This result indicates that traditional simulation techniques (e.g., DES, SD) and software tools (e.g., Arena, Anylogic, Simulink) are still applicable in I4.0. The results also indicate hybrid simulation and digital twin as the main simulation approaches in the context of I4.0. This result is consistent with the increasing trend to adopt hybrid modeling and simulation as a mean to meet the complex systems identified by Jahangirian et al. (2010). It is also consistent with the rising profile of digital twin along to the advancement of I4.0 identified by Tao et al. (2018a).

4.5.2 RQ2 – What are the purposes, empirical nature, and applications areas of studies on simulation in I4.0?

To address the second research question, the main purpose of the simulation-based studies in I4.0 is prescription and prediction for an improved mode of operations. However, most studies use artificial data or hypothetical cases (i.e., hypothetical problem-solving). This finding may be partly due to the novelty of I4.0 and the early development stage of simulation in I4.0. It may also be explained by the fact that it is often difficult and time-consuming to collect primary data from physical systems that are usable for simulation-based research or owing to restrictive confidentiality agreements.

For application areas, we found that studies on process engineering manufacturing, scheduling, and production planning and control are predominant. This result is in partially consistent with those obtained in Shafer and Smunt (2004) and Jahangirian et al. (2010), which features scheduling as a dominant research topic in simulation.

4.5.3 RQ3 – What are the design principles of I4.0?

For the third research question, the results indicate 17 design principles characterizing the I4.0 (see Fig.4.7). This result extends the list of principles identified in Ghobakhloo (2018), revealing other important research constructs, such as flexibility, agility, and autonomy, widely investigated in operation and supply chain management literature. This result is significant to guide companies in identifying and implementing I4.0 scenarios in a more practice-oriented manner, considering that it still lacks a clear understanding of the I4.0 concept (Hofmann and Ruesch, 2017; Moeuf et al., 2018). It is also important to support the development of modular and reusable simulation frameworks for a set of problems based on a library of software components that can be built upon the principles of I4.0.

4.5.4 RQ4 – Which I4.0 design principles are captured by each simulation-based approach?

Finally, for the fourth research question, the results suggest that simulation can fully or partially capture all design principles of I4.0. This result indicates that simulation can support the investigation of the I4.0 phenomenon from multiple perspectives (e.g., strategic, tactical, operational), suggesting a broader set of applications from the ones already reported in the literature. This result is essential to foster the simulation's adoption to capture and solve problems that emerge in the context of I4.0, to support the assessment and guide the implementation of I4.0, wherein there is still a lack of tools for practitioners and managers, as pointed by Hofmann and Ruesch (2017). However, the extensiveness wherein I4.0 principles are captured varies according to each simulation-based approach. In this regard, hybrid simulation and digital twin stand as the most promising approaches for I4.0 because they are able to capture most principles of I4.0. However, traditional simulation approaches such as DES are still valid and will continue to evolve driven by I4.0, as discussed by Vieira et al. (2018), which proposes a research agenda for DES in I4.0.

4.6 Limitations and future research

Similar to other studies, this review has its limitations, one of which relates to the search strategy. As discussed by Liao et al. (2017), there are other similar I4.0 initiatives, such as the Industrial Internet of Things (IIoT), developed in the USA, a term that could be used in queries considering that some authors use these terms interchangeably (Hofmann and Ruesch, 2017). However, these issues were partially addressed using the backward and forward snowball sampling technique (Wohlin, 2014) and by including a high number of articles in the sample, compared to other reviews in the field of I4.0 and simulation, such as the ones developed by Moeuf et al. (2018) and Vieira et al. (2018). Furthermore, the study focuses only on peer-reviewed journal articles. Other document types, sources of data and languages could be considered in the search protocol. Moreover, this study is not an exhaustive review of each simulation-based approach. Future studies can focus on a particular simulation technique, such as the one developed by Vieira et al. (2018), which proposed a research and development agenda for DES in I4.0.

A limitation of this study related to analysis is that content analysis (i.e., categorization and compilation of data) involves subjective judgment calls. However, by using the PRISMA statement (Moher et al., 2009), triangulation by investigators (Bengtsson, 2016), and existing classification categories (Harrison et al., 2007; Jahangirian et al., 2010) we have minimized the potential bias of reviewers. In addition, this study does not investigate all the relationships (and or dependencies) and aggregation levels between the design principles of I4.0. This can be addressed in future studies.

The analysis of the results also reveals issues and opportunity areas for future research:

- Hybrid modeling and simulation: different forms of model hybridization (e.g., multi-methods, multi-models, composite models) can be explored in future researches to manage the increasing complexity of I4.0 manufacturing systems. However, problems such as incompatibilities between simulation software tools, conflicts between distributed heterogeneous data sources, interface incompatibility, incompatible runtime models and multiple representations of time, bases of value, bases of behavior and resolutions (Mustafee et al., 2015; Eldabi et al., 2018; Tao et al., 2018a), related to models interoperability and synchronization will require addressing.

- Data-driven and real-time simulations: incorporating real-time data or big data into the simulation models and developing real-time optimized simulations is a research trend that can advance I4.0 towards its vision of real-time self-optimized production systems.

In this regard, there are several opportunities to integrate artificial intelligence techniques (e.g., genetic algorithms, artificial neural networks, reinforcement learning) as well as other machine learning and deep learning techniques into simulation models. Simulation models can embed artificial intelligence components to allow testing, calibration, forecasting, optimization, learning, or adaptive behavior and to increase the speed of large-scale models (Wallis and Paich, 2017).

- Real problem solving: most simulation-based studies in I4.0 use either artificial data or hypothetical cases. Therefore, the development of real cases using real-world data from industry is required to increase the practical relevance of simulation research in the context of I4.0 and to bridge the gap between academic studies and industry practices. Because most companies are not Industry 4.0-ready, as discussed by Schlechtendahl et al. (2014), the use of learning factories (or living labs) to develop testbeds and or proof-of-concept experiments can be considered, as applied in Zhou et al. (2019) and Schluse et al. (2018).

- The purpose of using simulation: most studies analyzed center on prediction or prescription (see Fig. 4.8c). There is a lack of models used for exploration, discovery, proof, critique, and empirical research guidance. In this regard, it is also important to highlight that simulation is a robust methodology to advance theory development (Harrison et al., 2007; Davis et al., 2007), and there remains sufficient room for simulation-based research in I4.0.

- Application areas: the lack of simulation studies in I4.0 related to critical areas of industrial engineering, operations, and supply chain management (e.g., just-in-time, cellular manufacturing, capacity planning, quality management) revels other future research avenues. An approach to partly address these problems, whereas using companies' capabilities is to combine Lean production practices with simulation techniques, which is consistent with earlier research (Lugert et al., 2018; Uriarte et al., 2020).

- Principles captured: the summary of I4.0 design principles described by the simulation models analyzed (indicated in Fig. 4.8e) introduces other research opportunities owing to the lack of models to describe principles such as smart products, corporate and social responsibility, horizontal integration, and end-to-end engineering integration, which requires significantly holistic approaches.

- Classification of models: the development of a new typology and or taxonomy for modeling and simulation in I4.0 is another promising avenues for future research because it can help reduce complexity (grouping several concepts into a small number of types) and make more accessible for researchers and practitioners to identify terminologies, define and categorize their models more accurately.

4.7 Conclusions and implications

Simulation is a key technology of Industry 4.0 to support the development of planning and exploratory models to optimize decision making, the design, and operations of complex systems. It also has the potential to aid the assessment and implementation of Industry 4.0 in companies by evaluating multiple scenarios. However, advancements in Industry 4.0 and its enabling technologies (e.g., the Internet of Things, Cyber-Physical Systems, Big Data) introduces new challenges to the field of simulation owing to the increasing complexity of systems to be modeled. This study aimed to provide a state-of-the-art review of simulation in the context of Industry 4.0.

This study shows an increasing trend in simulation-based research in Industry 4.0 within the last four years and suggests that the research area at the intersection of Industry 4.0 and simulation fields will likely continue to grow owing to its increasing relevance to the industry. In total, 10 simulation-based approaches employed in Industry 4.0, and 17 design principles characterizing the Industry 4.0 were identified. A cross-analysis of concepts show that all design principles of Industry 4.0 can be fully or partially expressed through simulation. Moreover, our findings suggest that hybrid simulation and digital twins are currently the two primary simulation approaches in Industry 4.0.

The findings from this study have implications for researchers, practitioners, and managers. The results suggest that simulation-based approaches can aid the investigation of the Industry 4.0 phenomena from different perspectives (e.g., strategic, tactical, operational). Furthermore, the use of simulation techniques can equip organizations with means to evaluate Industry 4.0 principles and technologies in a virtual environment to enhance technology investment decision-making and aid the transition toward the 4th Industrial Revolution.

Finally, despite the limitations of this review, we believe it will contribute to the work of researchers and practitioners striving to understand the state-of-the-art of research at the intersection between the emerging field of Industry 4.0 and the field of simulation by identifying, characterizing and analyzing simulation-based research developed in the context of Industry 4.0 and by discovering opportunities for future research.

CHAPTER 5 ARTICLE 2: A FRAMEWORK FOR IDENTIFYING AND ANALYZING INDUSTRY 4.0 SCENARIOS

"*The dynamics of any system can be explained by showing the relations between its parts and the regularities of their interactions so as to reveal its organization. For us to fully understand it, however, we need not only to see it as a unity operating in its internal dynamics, but also to see it in its circumstances, i.e., in the context to which its operation connects it" (Maturana and Varela, 1987, p. 58)*

This chapter presents a framework to facilitate the identification and analysis of Industry 4.0 application scenarios and examples to support the development of Industry 4.0 initiatives in manufacturing companies, extending the analytical framework described in the previous chapter. The manuscript contained in this chapter was co-authored[1] with my research director, Prof. Fabiano Armellini, my co-research director, Prof. Luis Antonio de Santa Eulalia, and the partner supervisor, director of research and partnership development, Vincent Thomasset-Laperrière. I am the first author, and my contribution is estimated at 90%. The manuscript was submitted to the double-blind peer-reviewed journal Computers & Industrial Engineering on May 24, 2021, and is currently under review as of December 21, 2021.

[1]**Author contributions:** William de Paula Ferreira: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. Fabiano Armellini: Methodology, Supervision, Validation, Funding acquisition, Writing - review & editing. Luis Antonio de Santa-Eulalia: Methodology, Supervision, Validation, Funding acquisition, Writing - review & editing. Vincent Thomasset-Laperrière: Resources, Supervision, Validation, Writing - review & editing.

A framework for identifying and analyzing Industry 4.0 scenarios

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Abstract: Industry 4.0 is a central strategy to strengthen the competitiveness of the manufacturing sector over the next years. Nevertheless, there is a lack of common understanding of the Industry 4.0 concept and tools to help companies' transformation to Industry 4.0, especially for small and medium-sized enterprises. To address these research gaps, this study proposes a framework to characterize and evaluate Industry 4.0 scenarios in order to aid companies' transition towards Industry 4.0. For this, a multi-methodological approach is adopted, including a review of several application examples of Industry 4.0 in companies reported in the literature and a proof-of-concept involving modeling and simulation, developed in collaboration with a centre for technological transfer in Quebec, Canada. The results indicate that the proposed framework can help companies identify Industry 4.0 scenarios more intuitively and assist project portfolio selection and planning during Industry 4.0 roadmap development. Finally, the results of this study suggest that Industry 4.0 can be implemented incrementally while companies increase their digital capabilities and maturity.

Keywords: Industry 4.0 Maturity Model, Roadmap, RAMI4.0, Use Cases, Discrete-Event and Agent-Based Simulation, AnyLogic®.

5.1 Introduction

Industry 4.0 (I4.0) is considered the main strategy to strengthen the competitiveness of the manufacturing sector over the next years (Kagermann et al., 2013; Schwab, 2017; PwC, 2016; Deloitte, 2018). It refers to “a collective term for technologies and concepts of value chain organization” (Hermann et al., 2015, p. 11), having implications for value creation, organizational performance, development of new business models, services and work organization (Kagermann et al., 2013; Lichtblau et al., 2015; Schwab, 2017; Xu et al., 2018). The I4.0 was triggered by the need to shorten development and innovation cycles, individualization of demand, and resource efficiency (Lasi et al., 2014), and is driven by significant advancements and access to emergent technologies, such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Big Data analytics (Schwab, 2017; Xu et al., 2018; Schneider, 2018).

However, there is still no common definition and understanding of the I4.0 concept (Liao et al., 2017; Moeuf et al., 2018), making it difficult for companies to plan I4.0 implementation effectively (Hofmann and Ruesch, 2017). Furthermore, there is still a lack of research about the risks, costs, revenue potential, implementation barriers, and tools to help companies’ transition towards I4.0 (Hofmann and Ruesch, 2017; Lugert et al., 2018; Müller et al., 2018; Fettermann et al., 2018; Bordeleau et al., 2020; Wagire et al., 2020; Tortorella et al., 2020), especially for small and medium-sized enterprises (SMEs). As revealed by Moeuf et al. (2018, p. 1132), “despite the growing number of new tools and technologies, most of them are under-exploited, if not ignored by SMEs”, which can prevent SMEs from remaining competitive in the digital global economy. There is a need to help SMEs to identify areas of their business that could be positively impacted by I4.0 design principle and cutting-edge technologies and how they should be implemented (Moeuf et al., 2018; Fitzgibbon, 2019).

Implementing I4.0 in companies is a complex and resource-demanding process, from the financial and organizational perspectives, involving significant changes in infrastructure, processes, operations, work organization, skill requirements, and business models (Lichtblau et al., 2015; Veile et al., 2019; Müller et al., 2018; Abar et al., 2017; Masood and Sonntag, 2020; Weking et al., 2020). Moreover, “there is no one-size-fits-all solution for companies” seeking to implement I4.0 (Lichtblau et al., 2015, p. 56). In this context, identifying and analyzing I4.0 scenarios effectively for implementation is essential to overcome challenges faced by companies (mainly SMEs) wishing to move toward I4.0, such as the lack of infrastructure, expertise, and scarcity of financial resources (Lichtblau et al., 2015; Da Silva et al., 2020; Stentoft et al., 2020; Ghadge et al., 2020). It may also facilitate communication with key stakeholders and simplify for companies to justify and vindicate funding from governmental programs that aims to foster the manufacturing sector’s competitiveness.

To contribute to reducing these research gaps and helping practitioners and managers in project portfolio identification and selection for implementing I4.0 scenarios in companies, the building blocks and practices of the I4.0 can be identified and used to systematize knowledge. A similar approach has been adopted to address the confusion and inconsistency related to the Lean Production concept (Shah and Ward, 2007), which is considered a multi-dimensional approach that encompasses several management practices used to improve a company's operational performance (Shah and Ward, 2003). Moreover, I4.0 use cases and/or showcases can be identified and shared in a structured way for benchmark, following another Lean Production practice known as Yokoten (Paris, 2010), which means sharing information and best practices within and across companies to facilitate Lean implementation. Furthermore, modeling and simulation can be used as tools to evaluate and gain insights about those I4.0 scenarios (Kagermann et al., 2013; de Paula Ferreira et al., 2020), which have not been considered in the existing I4.0 roadmap (Pessl et al., 2017; Ghobakhloo, 2018; Peukert et al., 2020).

Therefore, this study aims to investigate the building blocks to implement I4.0 and propose a framework to characterize and evaluate I4.0 scenarios in a more practice-oriented manner to help clarify the understanding of the I4.0 concept and support SMEs' transition toward I4.0. For this, a design science (multi-methodological) approach is adopted, including a review of Industry 4.0 cases and a proof-of-concept case involving modeling and simulation. This study's scope is limited to manufacturing industries, following I4.0 initial (Kagermann et al., 2013), focussing on SMEs and the technological dimension of I4.0.

The contributions of this study are twofold. First, it proposes a framework for identifying I4.0 scenarios more intuitively, addressing part of the research gap/opportunity pointed in different studies (Hofmann and Ruesch, 2017; Lugert et al., 2018; Tortorella et al., 2020; de Paula Ferreira et al., 2020). In this sense, to clarify and exemplify what I4.0 scenarios are, this study provides a review of several application examples of I4.0 in companies reported in the literature, which helps elucidate the fuzziness of understanding about the term I4.0. Second, it presents a framework for analyzing I4.0 scenarios that incorporates modeling and simulation as a supporting tool for project portfolio selection and planning during I4.0 roadmap development, which is unexplored by existing I4.0 roadmaps (Pessl et al., 2017; Ghobakhloo, 2018; Peukert et al., 2020). To demonstrate its usefulness and ease-of-use, the paper presents a proof-of-concept case developed in a college centre for technology transfer (CCTT) in Quebec, Canada, applying the overall proposed approach.

The remainder of this paper is organized as follows. Section 5.2 presents the research background and describes the essential building blocks to implement the I4.0 in companies. Section 5.3 describes the research methodology. Section 5.4 presents the general framework to support the implementation of I4.0 and the frameworks for identifying and analyzing I4.0 scenarios. Section 5.5 presents the proof-of-concept developed in collaboration with a college centre for technology transfer (CCTT) in Quebec, Canada. Section 5.6 presents the discussion. Finally, conclusions and opportunities for future research are outlined in Section 5.7.

5.2 Background

We reviewed the literature on I4.0 implementation, identifying the essential building blocks to support companies' transition towards I4.0 (i.e., maturity model, roadmap, reference architecture). Then we combined those building blocks with modeling and simulation to propose a general framework for I4.0 realization, which is introduced in Section 5.4.

5.2.1 Maturity model

The I4.0 maturity model (also referred to as readiness assessment model) is an artifact used to evaluate the degree of readiness of an organization to adopt/implement the I4.0 strategy and/or evaluate the maturing state of an organization in its journey towards I4.0 (Lichtblau et al., 2015; Schumacher et al., 2016; Wagire et al., 2020). The assessment of readiness and maturity is considered the first step for implementing I4.0 (Wagire et al., 2020), which can be performed through a company's self-assessment or collaborative assessment with the help of a consulting firm (Schumacher et al., 2016; Scremin et al., 2018).

There are over 13 different I4.0 maturity and/or readiness models available in literature (Mittal et al., 2018; Wagire et al., 2020), of which the ones proposed by Schumacher et al. (2016), Schuh et al. (2017) and Lichtblau et al. (2015) are the three most cited. They are composed of maturity dimensions, maturity measurement items, and maturity score levels (Wagire et al., 2020). As an example, Schumacher et al. (2016) maturity model is composed of a total of 38 items, divided into 9 dimensions of I4.0 (i.e., strategy, technology, operations, leadership, customers, products, culture, people, governance), and classify a company's degree of I4.0 implementation into 5 levels.

Overall, a maturity model can be mathematically represented by a set of maturity measurement items $I = \{1, ..., n\}$ divided into partitions P_d representing $d \in D = \{1, ..., r\}$ dimensions of I4.0. An organization's maturity score levels can be calculated into three steps based on a closed-ended structured survey conducted with a group $E = \{1, ..., e\}$ of industry experts. First, the importance weight g_{di} of each maturity item $i \in S_d$ is defined based on the average of the ratings x_{die} from all experts $e \in E$ recorded on a four-point Likert scale

(1 = not important and 4 = very important) using Equation 5.1.

$$g_{di} = \frac{1}{|E|} \sum_{e \in E} x_{die} \qquad \forall\, d \in D,\ i \in P_d \tag{5.1}$$

Second, the maturity level for each measurement item l_{di} is calculated based on the average of the score y_{die} attributed for all experts $e \in E$ for each item $i \in P_d$ recorded on a five-point Likert scale (0 = not implemented and 5 = fully implemented), assuming equal weight for all respondents, using Equation 5.2.

$$l_{di} = \frac{1}{|E|} \sum_{e \in E} y_{die} \qquad \forall\, d \in D,\ i \in P_d \tag{5.2}$$

Third, the maturity score level for each I4.0 maturity item m_{di} is calculated using the weighted average in Equation 5.3.

$$m_{di} = \frac{l_{di} \times g_{di}}{g_{di}} \qquad \forall\, d \in D,\ i \in P_d \tag{5.3}$$

Additionally, the maturity score level for each I4.0 maturity dimension m_d and the overall maturity score m can be computed by the weighted average in Equation 5.4 and 5.5 respectively.

$$m_d = \frac{\sum_{i \in P_d} (l_{di} \times g_{di})}{\sum_{i \in P_d} g_{di}} \qquad \forall\, d \in D \tag{5.4}$$

$$m = \frac{\sum_{d \in D} \sum_{i \in P_d} (l_{di} \times g_{di})}{\sum_{d \in D} \sum_{i \in P_d} g_{di}} \tag{5.5}$$

It is important to mention that the I4.0 roadmap proposed by Schumacher et al. (2019) includes a maturity gap analysis, where not just the as-it-is state but target-state for each maturity item needs to be defined and analyzed to prioritize development items for I4.0 projects realization in companies.

5.2.2 Roadmap

The I4.0 roadmaps (also referred to as process models or procedure models) enable organizations to establish a detailed set of guidelines on the steps to take for achieving higher I4.0

maturity levels more effectively (Peukert et al., 2020). It is a tool for multidisciplinary teams to define a "chronological sequence of the planned measures in the form of concrete projects" (Pessl et al., 2017, p. 196), considering short, medium, and long term strategies to foster the implementation of I4.0 in companies (Ghobakhloo, 2018; Peukert et al., 2020).

There are more than 10 roadmaps for the implementation of I4.0 available in literature (Beaudoin et al., 2016; Pessl et al., 2017; Hermann et al., 2016; Ghobakhloo, 2018; Schumacher et al., 2019; Peukert et al., 2020), which are composed of different phases (e.g., analysis, objective, implementation) and different project management and creativity techniques, such as brainstorming, SWOT (strengths, weaknesses, opportunities, and threats) analysis, business model canvas, balanced scorecard, and cost-benefit analysis (Peukert et al., 2020; Pessl et al., 2017). The majority of these I4.0 roadmaps follow a project portfolio management (PPM) approach that refers to "the continuous process of selecting and managing the optimum set of project-oriented initiatives that deliver the maximum in business value or return on investment" (Miller, 2002, p. 1). PPM problems can be addressed through different modeling methods, such as comparative, scoring, optimization, and simulation methods, the latter being the least explored in literature (Mohagheghi et al., 2020).

As an example, Beaudoin et al. (2016) proposed an I4.0 roadmap for SMEs based on six steps: 1 - define a transition strategy (process, product, services); 2 - select one or more activities that can be improved through an I4.0 project; 3 - define the scope for an I4.0 project (monitoring, control, optimization, autonomy); 4 - choose the I4.0 technologies and techniques to be deployed; 5 - implement the I4.0 project; 6 - Assess the gains of the I4.0 project and launch the next I4.0 initiative. This process is repeated until companies reach desired I4.0 maturity levels. The authors also highlight the essential role of leadership, project management, and technical competencies to ensure a company's successful transition toward I4.0.

It is important to highlight that a fundamental activity considered in these I4.0 roadmaps is to define applicable I4.0 scenarios for realization in companies.

Industry 4.0 scenarios

I4.0 provides manufacturing companies with endless possibilities to innovate and improve their performance (Kagermann et al., 2013; Schwab, 2017). Nevertheless, most of them, especially SMEs, are still in the beginning of their I4.0 journey and will approach I4.0 incrementally through pilot projects (Schlechtendahl et al., 2014; Moeuf et al., 2018; Peukert et al., 2020). An I4.0 scenario reflects one or more design principles and enabling technologies characterizing the I4.0, serving as a conceptual model for developing I4.0 practical applications (Hermann et al., 2015, 2016; Hofmann and Ruesch, 2017; Ghobakhloo, 2018; Peukert et al., 2020). It refers to or helps the conception of a technology-based project that can be roadmapped for developing an I4.0 use case in a company, which can later become a showcase for other areas or companies (Peukert et al., 2020).

The first studies to propose a conceptual model to support the identification of I4.0 scenarios for implementation in companies are Hermann et al. (2015) and Hermann et al. (2016). These studies conducted a systematic literature review and meta-analysis to identify the main design principles and enabling technologies of I4.0, arguing that those I4.0 components may be used to identify, describe, and select I4.0 scenarios for further investigation but that "further research should challenge their utility by identifying, describing, and selecting Industrie 4.0 scenarios from an academic or practical perspective" (Hermann et al., 2016). It is worth mentioning that the list of I4.0 principles and technologies has been updated in Ghobakhloo (2018) and de Paula Ferreira et al. (2020).

Another model for I4.0 scenarios is proposed by Anderl et al. (2016), which follows a use case approach, focussing on manufacturing companies' value-added processes. They classify the I4.0 application scenarios into seven categories: order-controlled production; adaptable factory; self-organizing adaptive logistics; value-based services; transparency and adaptability of delivered products; operator support in production; smart product development for smart production; innovative product development; and circular economy. It is important to notice that Anderl et al. (2016) make a distinction between the I4.0 implementation scenario and the I4.0 application example, where the first refers to a generic description of a user's problem and the latter to a particular solution for a user. In summary, I4.0 implementation scenarios can lead to multiple I4.0 application examples (Anderl et al., 2016). Similarly, Weking et al. (2020) proposed a business model pattern framework for I4.0, identifying 13 patterns of I4.0 business models, which can be used to guide manufacturing companies towards I4.0.

It is important to point out that in order to implement I4.0 scenarios consistently, ensuring interoperability to make information flow from products and field devices to the connected world based on vertical, horizontal, and end-to-end integration, it is crucial to adopt a reference architecture (Adolphs et al., 2015; Moghaddam et al., 2018).

5.2.3 Reference architecture

There are different reference architectures related to I4.0 (Moghaddam et al., 2018; Li et al., 2018), of which the RAMI4.0 (Reference Architecture Model for Industry 4.0) is gaining broad acceptance in academy and industry, providing a blueprint for I4.0 implementation. The RAMI4.0 is essentially built upon existing standards and methods from ICT and production fields, such as ISA-95 (international standard for enterprise control systems integration) and agent technology (Adolphs et al., 2015; Moghaddam et al., 2018).

The RAMI4.0 represents I4.0 domain in three dimensions: (1) layers: asset, integration, communication, information, functional, business; (2) life cycle & value stream; and (3) hierarchy levels: product, field device, control device, station, work centres, enterprise, connected world (Adolphs et al., 2015). It extends ISA-95 (IEC 62264) hierarchy levels (also referred to as the automation pyramid) by adding the product level at the bottom and connected world level at the top of the pyramid (Adolphs et al., 2015; Li et al., 2018; Moghaddam et al., 2018). Overall, RAMI4.0 combines the “life cycle and value stream with a hierarchically structured approach for the definition of I4.0 components” (Adolphs et al., 2015, p. 6), which designates the agents (physical or virtual object) in the system, endowed with communication ability and technical functionality (Zezulka et al., 2016; Moghaddam et al., 2018).

It is important to emphasize that RAMI4.0 development is grounded in agent and holonic paradigms to modeling manufacturing systems (Moghaddam et al., 2018). Moreover, modeling and simulation techniques may provide important insights about RAMI4.0 application and act as an enabler for managing I4.0 complex systems (Kagermann et al., 2013).

5.2.4 Modeling and Simulation

Modeling and simulation is a primary research methodology in the fields of operations management and industrial engineering (Bertrand and Fransoo, 2002; Shafer and Smunt, 2004; Davis et al., 2007; Negahban and Smith, 2014; Scheidegger et al., 2018; de Souza Dutra et al., 2020; de Paula Ferreira et al., 2021) and can be used to analyze the I4.0 phenomenon (Kagermann et al., 2013; Mourtzis, 2020; de Paula Ferreira et al., 2020). It denotes a set of techniques for designing a model (abstract and simplified representation) of a real or hypothetical system for conducting computational experiments with the model in a risk-free environment for prediction, proof, explanation, prescription, empirical guidance, among other applications (de Assis et al., 2021; de Paula Ferreira et al., 2020; Harrison et al., 2007).

The state-of-the-art review conducted by de Paula Ferreira et al. (2020) describes 10 simulation-based approaches applied to the context of I4.0, of which hybrid simulation (HS) that combines discrete-event simulation (DES) with agent-based modeling and simulation (ABMS) is the focus of this study. It considers that I4.0 components development is rooted in the notion of agent technology (Moghaddam et al., 2018) and that HS is the primary approach used in I4.0 (de Paula Ferreira et al., 2020).

HS (ABMS + DES) provides a bottom-up approach to modeling systems (Brailsford et al., 2019), where the DES model represents the process flow and the ABMS model to substitute DES passive entities to certain active entities, considering individual agents behaviors and autonomy (Siebers et al., 2010; Scheidegger et al., 2018; Da Costa et al., 2017; Brailsford et al., 2019). It considers both an agent perspective and a process perspective to define the model implementation. From Siebers et al. (2010, p.207), true ABMS in operational research (OR) that focusses on decision support and problem-solving does not exist; combined applications of ABMS with DES "seems to be the way forward to tackle the problems in what becomes more an investigation into behavioral OR due to the recent shift of attention from manufacturing to service industry."

ABMS is a bottom-up, decentralized approach, where agents are modeled and implemented in a computer simulation, and their interactions may produce observable global emergent behaviors (Macal and North, 2010; Santa-Eulalia et al., 2011). An agent can be defined as a complex software unit endowed with attributes and methods (Barbati et al., 2012; Abar et al., 2017). It consists of "autonomous component that represents physical or logical objects in the system, capable to act in order to achieve its goals, and being able to interact with other agents, when it does not possess knowledge and skills to reach alone its objectives" (Leitão, 2009, p. 982). The agent-based simulation (ABS) executes an agent-based model (ABM) of a multi-agent system (MAS) to study the behavior of certain parameters of the model or environment on interest values (Siebers et al., 2010; Barbati et al., 2012; Frayret, 2011). ABMS is a type of application of MAS, both part of agent technology, whose domain of applications is larger than simulation (Frayret, 2011).

5.3 Methodology

This study is theoretically grounded in design science research, which is widely used for the development and evaluation of new artifacts (e.g., models, frameworks) to solve relevant open problems innovatively or more effectively (Hevner et al., 2004; Peffers et al., 2007). An overview of the research design is shown in Fig. 5.1, following the Hevner et al. (2004) and Mitroff et al. (1974) guidelines.

The research design shown in Fig. 5.1 comprises a multi-methodological approach to developing a framework for identifying and analyzing I4.0 scenarios for I4.0 realization. It includes a literature review on I4.0 implementation building blocks, a review of I4.0 real cases of implementation in companies, and a proof-of-concept case study developed in a technological transfer centre integrating modeling and simulation.

This study counts with primary and secondary data collected from a college centre for tech-

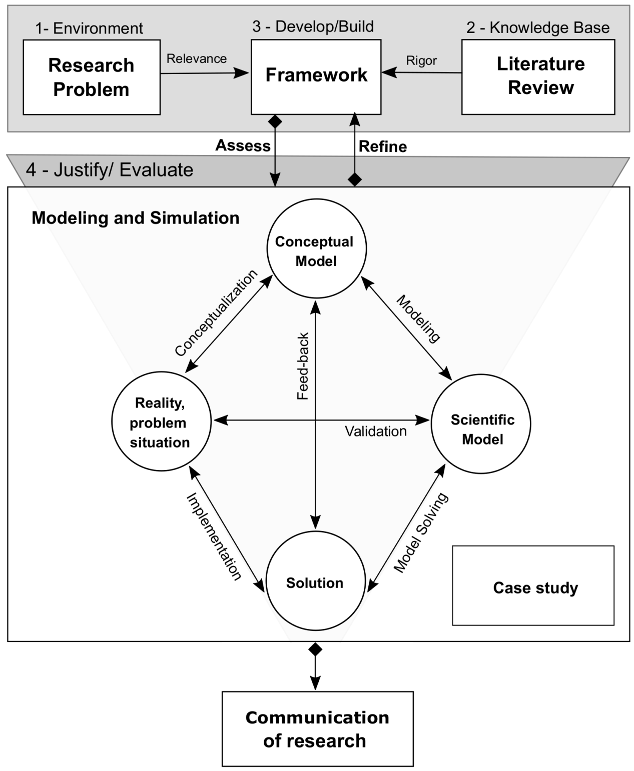


Figure 5.1 Research design.

Source: Adapted from Mitroff et al. (1974) and Hevner et al. (2004).

nology transfer (CCTT) and four SMEs assisted by the CCTT, located in the province of Quebec, Canada, engaged in the transition toward I4.0. The CCTT was selected as a research setting since its primary role is to aid manufacturing SMEs' transition toward I4.0, matching this article's research scope. Moreover, the CCTT adopts a living lab and triple helix collaboration approach, which involves academic institutions (i.e. college, university), government, and industry, being supported by an extensive network of manufacturing SMEs, serving as a realistic test case for SMEs industrial-scale situations. Additionally, several cases with application examples of I4.0 in companies were identified through the Web of Science, Scopus, and Google Scholar electronic databases and analysed qualitatively to support the validity of the proposed framework and to gain in-depth insights about I4.0 implementation, following a case survey methodology (Larsson, 1993).

Specifically, the data collected for the proof-of-concept case include direct observation during participation in CCTT weekly meetings related to I4.0 projects for six months, manufacturing and process data from their living lab, semi-structured interviews, and surveys conducted with industry experts associated with the CCTT that are directly involved in I4.0 research, development, maturity assessment, or technical assistance to guide SMEs towards I4.0. It also includes business process and maturity assessment data from four manufacturing SMEs collected by the CCTT to support the case selection and contextualization for enabling posterior technological transfer. Further details on the methodology are provided in the next sections.

5.4 General framework

Fig. 5.2 presents the general framework to guide I4.0 scenarios implementation in companies, which combines three essential building blocks for I4.0 realization (i.e., maturity model, roadmap, reference architecture) with modeling and simulation as a supporting tool, that is still unexplored by existing I4.0 roadmap aiming to help the deployment of I4.0.

The first step consists of performing an assessment of the organization using an I4.0 maturity model. Then, based on the maturity levels and business strategy, a company can perform a maturity gap analysis, as proposed by Schumacher et al. (2019) to prioritize maturity items for development and define its roadmap to reach higher I4.0 maturity levels, defining I4.0 scenarios for implementation. This phase relates to technology project portfolio management, as discussed by Peukert et al. (2020). At this stage, I4.0 scenarios (or I4.0 projects) can be identified and selected for evaluation through modeling and simulation to support project portfolio selection and planning. Thereafter, the simulation experiments' results can be feedback to refine the I4.0 roadmap for realization. Lastly, if the case, the results obtained with the implementation of the I4.0 scenario in a company can be feedback for verification, validation, and improvement of the simulation model.

The RAMI4.0 reference architecture relates to the other elements in Fig. 5.2 in different ways, being part of the foundation that all other elements should be built. First, RAMI4.0 gathers the essential aspects of I4.0 and provides a common ground for organizations and multidisciplinary teams on how to approach I4.0 implementation in a structured manner (Adolphs et al., 2015; DIN SPEC 9134, 2016). Moreover, it serves as a basis for developing or refining I4.0 maturity models, as described in Weber et al. (2017). Furthermore, RAMI4.0 can be used to translate I4.0 scenarios identified during the roadmap development from high abstraction levels to engineering requirements for implementation in companies by abstracting and linking I4.0 architectural aspects to proven industry standards, such as IEC62890, IEC 62264, and IEC 61512/ISA 95 (DIN SPEC 9134, 2016). One can access the list of industry standards considered in RAMI4.0 at `http://i40.semantic-interoperability.org/`. In addition, RAMI4.0 provides recommendations of technologies and guidelines for modeling I4.0 systems encompassing technological and human aspects (Adolphs et al., 2015; Moghaddam et al., 2018; Platform Industrie 4.0, 2017).

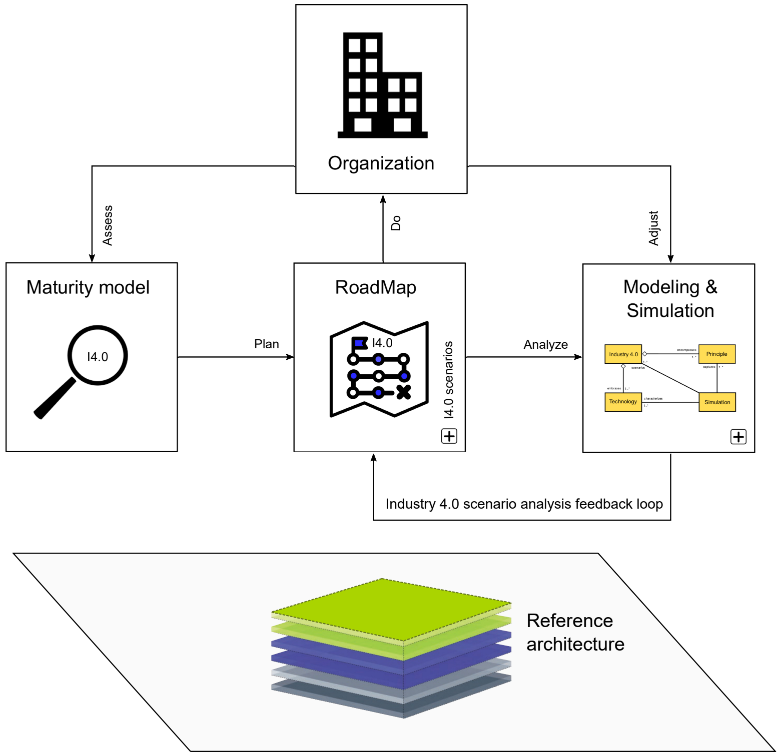


Figure 5.2 General framework to support Industry 4.0 implementation

The next two subsections present the frameworks to help to identify and analyze I4.0 scenarios for realization in companies, representing two subprocesses of the general framework as indicated in Fig. 5.2 by the $\boxed{+}$ symbol, where this study's main contributions reside.

5.4.1 A framework for identifying Industry 4.0 scenarios

Fig. 5.3 presents a conceptual framework to help manufacturing companies operationalize the I4.0 concept and identify I4.0 scenarios for realization more intuitively. It is composed of four blocks of constructs. The first block indicates the design principles of I4.0, adopted from de Paula Ferreira et al. (2020). The second block refers to the enabling technologies of I4.0, compiled from Ghobakhloo (2018), Alcácer and Cruz-Machado (2019), and Bongomin et al. (2020). The third block relates to the main sub-areas of industrial and operations management, adopted form Shafer and Smunt (2004) and Jahangirian et al. (2010). The fourth block presents some of the main performance measures used by manufacturing companies (Marodin and Saurin, 2013; Frederico et al., 2021), associated with the expected benefits of I4.0 (Dalenogare et al., 2018; Fatorachian and Kazemi, 2018).

It is important to highlight that each block may include other elements, considering the

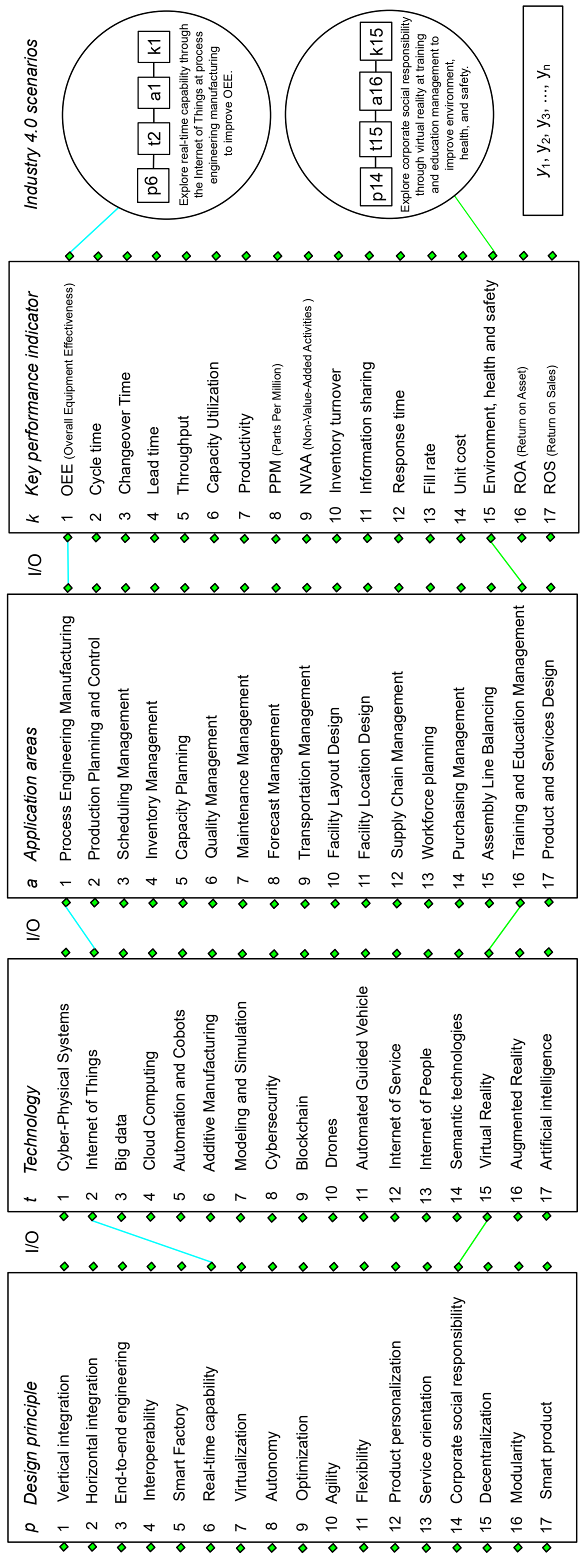


Figure 5.3 Industry 4.0 scenarios identification framework

continuous advancement of I4.0 enabling technologies and practices (Schwab, 2017). Furthermore, there are over 100 metrics (e.g., operational, economic, environmental) available in the literature that can be considered for performance evaluation at the strategic, tactical and operational levels, depending on contextual factors (Bhagwat and Sharma, 2007; Ramesh and Kodali, 2012; Marodin and Saurin, 2013; Kamble et al., 2020; Frederico et al., 2021).

The process for identifying an I4.0 scenario consists of selecting one or more elements of any of the four blocks in Fig. 5.3 and connecting it with one or more elements of at least two other remaining blocks and by following a simple gap-filling natural language generation approach. The main template used to generate the I4.0 scenarios is presented in Table 5.1. After that, the I4.0 scenarios can be analyzed and translated from high abstraction levels to low abstraction levels by following the RAMI4.0 (Adolphs et al., 2015; Sharpe et al., 2019), which helps identify the most relevant industry standards to be combined with the respective front-end and back-end technologies for its implementation in a company.

Table 5.1 Main template

What?	How?	Where?	Why?
Explore <principle>	through <technology>	at <application area>	to improve <kpi>

Table 5.2 Industry 4.0 use cases

Reference	Number of cases
Plattform-I4.0 (2020)	198
AIF (2020)	175
RRI (2020)	163
Fettermann et al. (2018)	38
Weking et al. (2020)	32
Tao et al. (2018b)	8
cri	2
DHL (2020)	1
Jensen et al. (2019)	1
Vieira et al. (2019b)	1
Total	619
Total - Duplicates	589

In order to test the proposed framework, thirty-four I4.0 scenarios were generated, following a stratified sampling, covering all principles and technologies in Fig. 5.3. Then, they were verified related to empirical evidence available in the literature. To identify the real cases of I4.0 implementation, a literature review was conducted in electronic databases searching: Web of Science, Scopus and Google Scholar from 2011 to 2020. Specifically, articles of which the title, abstract, or keyword include "Industry 4.0" or "Industrie 4.0" and "case stud*" or "use case*" or "show case*" or "application scenario*" were searched.

The article's reference list (backward snowball sampling) and citations to the article (forward snowball sampling) were then analyzed to identify additional relevant references (Wohlin, 2014). Only cases with company names were considered to verify and identify complementary information (e.g., company size, location) in the company's websites or other publications related to the case. In total, 578 cases of I4.0 implementation were identified, as summarised in Table 5.2. The I4.0 scenarios and use cases analyzed to test the proposed framework are available in Appendix B.

The generation of I4.0 scenarios linked to existing real cases of I4.0 implementation for benchmarking is a practical approach that may help manufacturing SMEs overcome some of the implementation barriers preventing them from moving towards I4.0, such as technology awareness limitations, knowledge resource limitations, and lack of clarity about I4.0 potential benefits, as pointed out by Lichtblau et al. (2015) and Masood and Sonntag (2020).

5.4.2 A framework for analyzing Industry 4.0 scenarios

As illustrated in Fig. 5.4, an I4.0 scenario, represents one or more I4.0 systems composed of I4.0 components, not I4.0 components, and people (Adolphs et al., 2015). The term component refers to a physical or virtual asset that is something of value for an organization (e.g., equipment, station, product, software, idea, service, document) and exerts a certain role in a certain system (DIN SPEC 9134, 2016). In the RAMI4.0, assets are mainly classified in terms of presentation (i.e., unknown, anonymously known, individually known, administered as entity) and communication capability (i.e., without, passive, active, I4.0-compliant) (DIN SPEC 9134, 2016). Based on this classification scheme, an I4.0 component, which characterizes an asset, is either: (1) anonymously known with passive communication capabilities; (2) individually known with I4.0-compliant communication; or (3) administered as entity with I4.0-compliant communication, where entity refers to uniquely identifiable asset managed in the information world (DIN SPEC 9134, 2016).

I4.0 components' properties include unambiguous identifiability, state in the lifetime (i.e. type, instance), I4-compliant communication capability via service-oriented architecture (SOA), virtual representation, technical functionality, nestability, and encapsulability (DIN SPEC 9134, 2016; Adolphs et al., 2015). Overall, I4.0-components are defined as "globally and uniquely identifiable participants capable of communication, and consist of the administration shell and the asset with a digital connection within an I4.0 system" (DIN SPEC 9134, 2016, p. 24). Essentially, the difference between a non I4.0 component from an I4.0 component is that the latter contains an administration shell, which records assets' lifecycle data and converts it into information, containing partial models from different domains (DIN

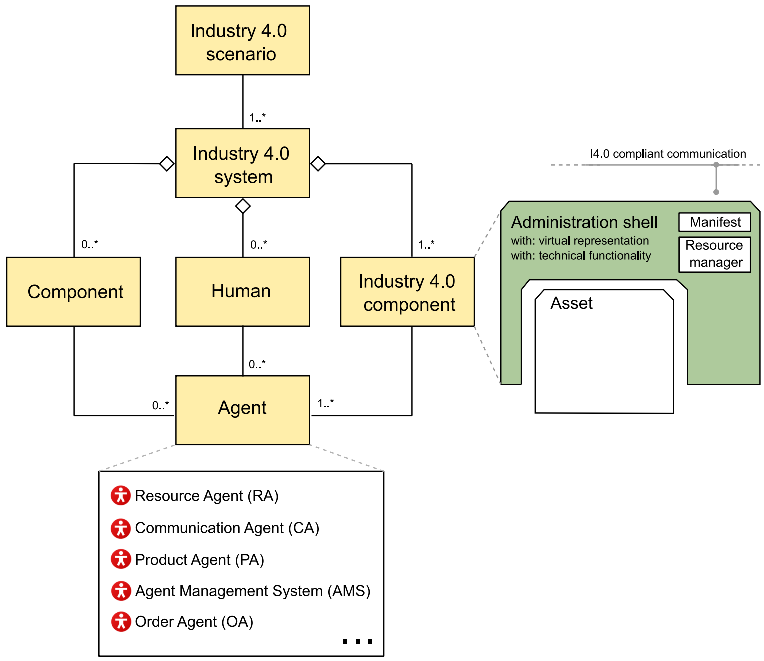


Figure 5.4 Industry 4.0 scenarios modeling.

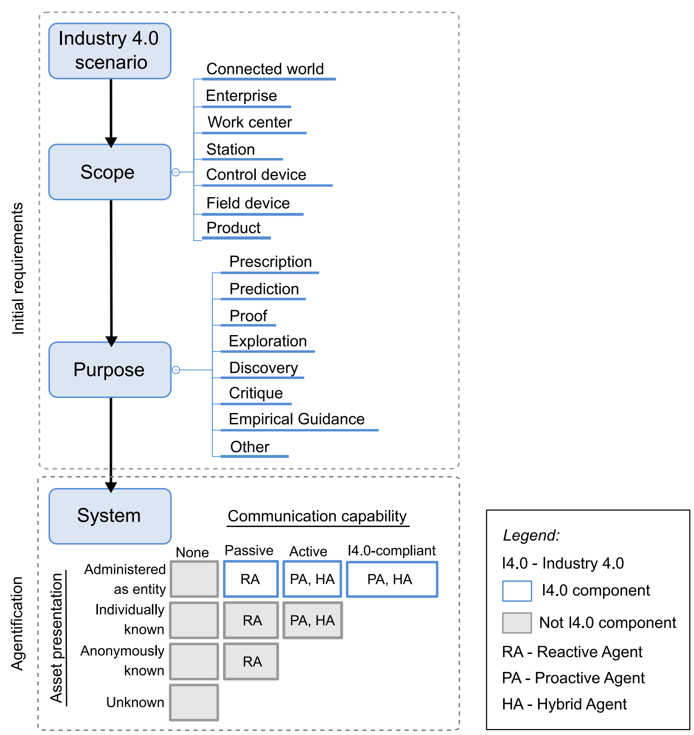


Figure 5.5 Guidelines for defining the simulation problem domain
Source: Adapted from Adolph et al. (2020).

SPEC 9134, 2016).

I4.0 systems can be analyzed through RAMI4.0 architecture, as described by Löwen et al. (2016), that modeled an I4.0 demonstrator based on RAMI4.0. A similar approach to model I4.0 systems in mini-factories context is proposed by Toro et al. (2020). I4.0 systems can also be analyzed using agent technology since its properties (e.g., autonomy, reactivity, proactiveness, social ability, reconfigurability, modularity, learning capacity), matches I4.0 components and systems requirements (Contreras et al., 2017; Salazar et al., 2019). Taking this into consideration and in order to support the analysis of I4.0 scenarios through simulation modeling we propose some assumptions and general guidelines presented in Fig. 5.5, addressing part of the conceptual modeling phase, which is of fundamental importance for the development of simulation studies (Macal and North, 2010; Santa-Eulalia et al., 2012). The main assumptions are as follows:

- There is an existing system non I4.0-compliant (base case scenario) for retrofitting based on the chosen I4.0 scenario (future state scenario);
- The chosen I4.0 scenario can be verified by domain experts involved in the project;
- There are proper resources available to develop the simulation project and enough time for the model results to be useful considering the decision-making time window.

Following Fig. 5.5 the first guideline is, after defining an I4.0 scenario, to define its scope of application, that is, the degree of granularity of the system for analysis based on the hierarchical levels of RAMI4.0 (i.e., product, field device, control device, station, work centres, enterprise, connected world), limiting system boundaries for modeling and analysis.

The second guideline is to specify the purpose or motivation for using simulation modeling relative to the I4.0 scenario since it influences simulation model design, i.e., conception, implementation, analysis (Santa-Eulalia et al., 2012; Macal and North, 2010). From Harrison et al. (2007) the use of simulation modeling can be classified into seven categories: (1) prediction — identify variables relationships and or making prognoses about future state; (2) proof — demonstrate that the modeled system can produce particular types of behaviors; (3) discovery — find emergent behaviors; (4) exploration — evaluate the conditions in which a certain behavior is produced; (5) critique — evaluate pre-existing explanations for a particular phenomenon; (6) prescription — establish improved modes of operation; (7) empirical guidance — assist theories development. Other motivations for using simulation modeling in manufacturing includes system performance analysis, problem-solving, achieving common understanding or resolving dispute between stakeholders, identification of system design requirements, selling an idea, training and education (Banks, 1998; Macal and North, 2010; Frayret, 2011; Mustafee et al., 2017; Scheidegger et al., 2018).

The third guideline is to identify the agents by distinguishing which assets composing the system to be modeled will be treated as I4.0 components and which will not, based on their presentation and communication capability, as represented in Fig. 5.5, as well as their technical function, representation, and state in the lifetime (i.e., type, instance). It's worth mentioning that humans are also an asset in the model context, which complies with Platform Industrie 4.0 (2017). Moreover, It is important to highlight that "what is modeled as an I4.0 component is a design decision" (Löwen et al., 2016, p. 19), as well as the agents. Nevertheless, for simulation modeling purpose, this procedure gives a good indication of candidates for agentification, their behaviors (i.e., reactive, proactive, hybrid), as described in (Wooldridge, 2009), and relationships, that are the main requirements to develop an agent-based model (Macal and North, 2010). A detailed description of assets hierarchical arrangement, aggregation, and relationships are provided in Platform Industrie 4.0 (2017) for reference. Another approach would be to adopt agent-based patterns and architecture for manufacturing, which enable the migration of legacy systems to I4.0 systems based on RAMI4.0, as proposed by Salazar et al. (2019).

In addition, it is recommended to use the business process modeling and notation (BPMN) and/or unified modeling language (UML) as primary conceptual modeling tools, since both modeling standards are widely used in the context of I4.0 and simulation modeling (Bersini, 2012; Siebers and Onggo, 2014; Adolphs et al., 2015; Scheidegger et al., 2018; Bocciarelli et al., 2019; Boss et al., 2019). In particular, we consider BPMN for mapping business process flow, UML class diagram for agentification, UML sequence diagram to describe agents' interactions, and UML state diagrams to describe agents' behaviors. For reference, the use of UML formalism to represent asset administration shell is described in Boss et al. (2019). The use of BPMN and UML for simulation modelling is described in several studies, such as in Bersini (2012), Siebers and Onggo (2014), Bocciarelli et al. (2019) and Scheidegger et al. (2018).

5.5 Proof-of-concept case

The proof-of-concept case of a college centre for technology transfer (CCTT) was developed with a focus on their living lab, where a testbed for I4.0 is being built to assist technological transfer to SMEs. It includes an automated storage and retrieval systems (AS/RS), a 90 degrees closed loop conveyor, a FANUC LR Mate 200iC robot arm, a CNC Lathe and CNC Milling machines from EMCO company, a 2D camera, and a UR5 collaborative robot (cobot) arranged in five stations to produce didactically prepared products.

The development of the case follows the general framework in Fig. 5.2. The first step was to assess the living lab's maturity level, also referred to as mini-factory. The CCTT has developed their own maturity model to assist SMEs. However, since the CCTT had not yet assessed the I4.0 maturity of its mini-factory and due to a non-disclosure agreement, we decided to adopt the self-assessment maturity model proposed by Lichtblau et al. (2015) due to its practicality, focus on I4.0 technological dimensions, and available dataset of I4.0 readiness levels of German SMEs for comparison. Nevertheless, any other maturity assessment model could be used at this stage.

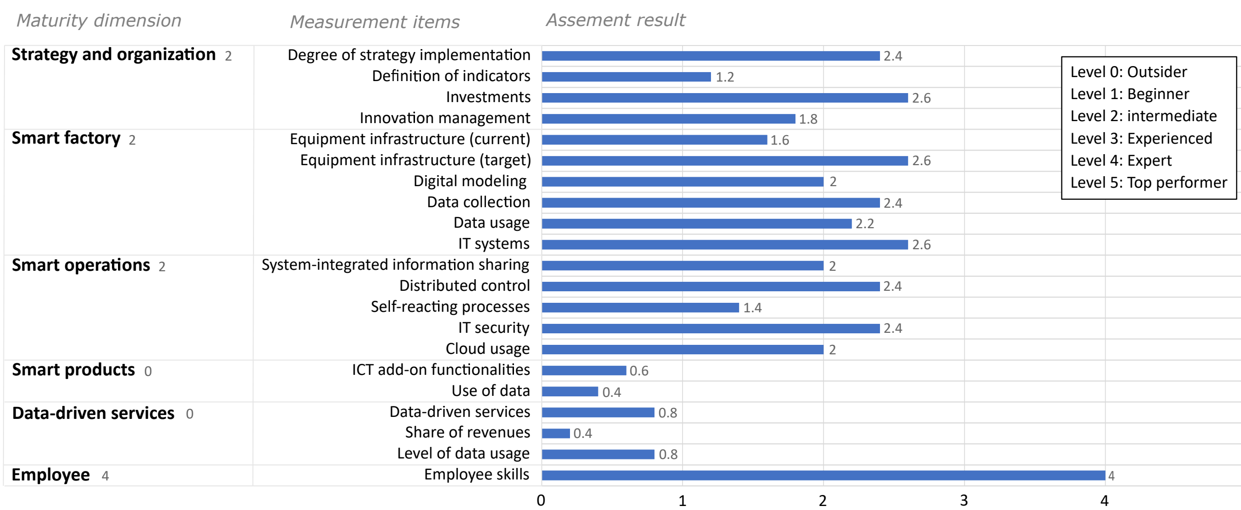


Figure 5.6 Industry 4.0 maturity assessment results

The I4.0 self-assessment was conducted with five project managers of the CCTT that have a comprehensive overview of the organization's strategy, following the Lichtblau et al. (2015) maturity model and calculation procedure described in Section 5.2.1. Based on the assessment results summarised in Fig. 5.6 and classifications in Lichtblau et al. (2015), the CCTT has an intermediate level of I4.0 readiness in the maturity dimensions strategy and organizations, smart factory, and smart operation, being classified as a learner; an outsider level in the dimensions smart products and data-driver services, classified as a newcomer; and an expert level in the dimension employee, classified as a leader. From the Lichtblau et al. (2015) available assessment dataset of manufacturing SMEs with up to 99 employees, only 6.5% have reached level 2 in strategy and organizations; 10.1% reached level 2 in the smart factory; 36.1% reached level 2 in smart operations; 83.1% are level 0 in smart products; 92.3% are level 0 in data-driven service; lastly, only 4.1% have reached level 4 in employee maturity dimension. These results suggest that even in its current state, the mini-factory can help the manufacturing SMEs reach higher I4.0 maturity levels. Nevertheless, much still needs to be done to promote I4.0.

After conducting the maturity assessment, we proceeded with a maturity gap analysis, as proposed by Schumacher et al. (2019), considering a five-year period, where the following maturity items were prioritized for development: definition of indicators, equipment infrastructure, digital modeling, data collection, data usage, IT-systems, distributed control, and self-reacting processes. The next step would be to define the roadmap for the CCTT, following any available model in the literature, such as the one proposed by Beaudoin et al. (2016), introduced in Section 5.2.2. However, the CCTT has already defined a roadmap for their mini-factory for the next five years, mainly based on project grants. Nevertheless, they have defined a few concrete initiatives, having much space to incorporate new I4.0 projects. Therefore, the I4.0 scenarios identification framework in Fig. 5.3 was applied to refine their existing roadmap, where a total of twenty-five I4.0 scenarios were generated and one selected based on the CCTT priorities for further analysis.

The I4.0 scenario identified through the framework in Fig. 5.3 selected for evaluation consists of exploring product personalization and smart product through the Internet of Things at process engineering manufacturing to improve capacity utilization. To give a better context, mass customization (or product personalization) is a manufacturing strategy that usually combines high production volumes with a high variety of products (Duray et al., 2000; James and Mondal, 2019). The approach to the manufacture of customized products (i.e., process, policies, technologies) depends on the customization configuration adopted, which can be identified and classified based on product modularity and the point of customer involvement for customization in the production cycle, i.e., design, fabrication, assembly, or use (Duray et al., 2000). In this sense, the mini-factory plans to adopt a cut-to-fit modularity approach based on parametric design, wherein customers can specify the dimensions and parameters changes to standard designs in the fabrication stage through a web application.

That being said, we proceeded with the application of the analysis framework in Fig. 5.4 and Fig. 5.5, limiting the scope of the I4.0 scenario selected for evaluation to the work centre that encompasses the five workstations. The main purposes chosen for the development of the simulation model were to define improved modes of operation (i.e., prescription); reach a common understanding between stakeholders; identify system design requirements; and education and training. The main assets composing the system to be modeled as I4.0 components are the order management system and smart products, managed as entities with active communication capabilities. Other important components are the processing machines and material handling equipment that are individually known components with active communication capabilities, therefore classified as non I4.0 components. Furthermore, based on Fig. 5.5 all these components can be modeled as hybrid agents.

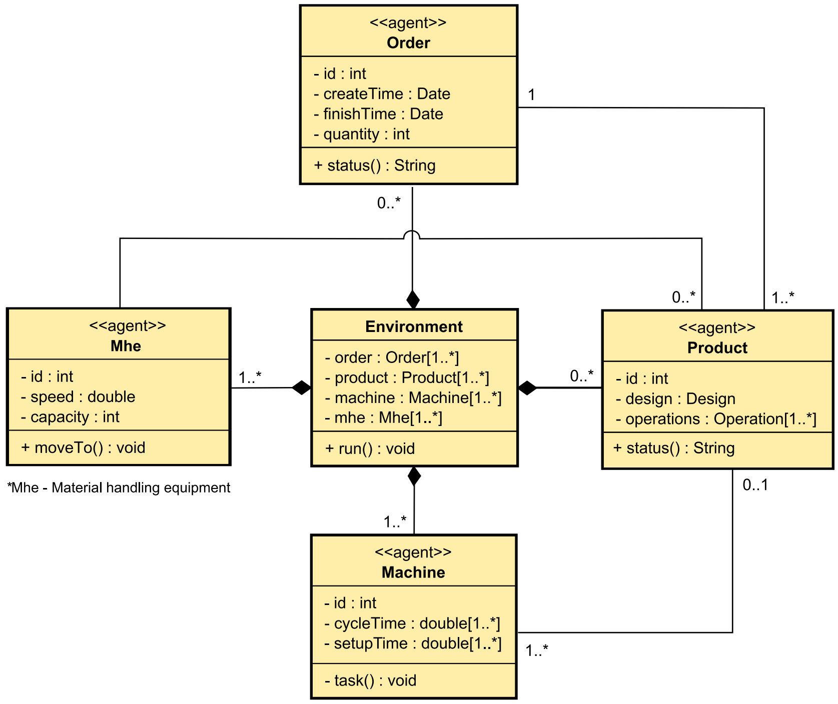


Figure 5.7 Simplified UML class diagram

Table 5.3 Input data for the simulation experiment

Agent Type	Extends from	Station	Processing time
AS/RS	Mhe Agent	1	32 seconds
CNC Lathe	Machine Agent	2	120 seconds
CNC Milling	Machine Agent	2	160 seconds
FANUC	Mhe Agent	2	30 seconds
2D Vision	Machine Agent	3	2 seconds
Worker	Operator	3	2 seconds
Conveyor	Mhe Agent	1 to 5	**

Legend: *Station where the machine is allocated. **Conveyor length = 18 metres, maximum speed = 0.7642 ft/sec, number of pallet carriers available = 15. Note: 2 buffer positions at station 2 and 4 buffer positions at station 4 are available in the future state scenario.

The agentification is represented in Fig. 5.7 as a UML class diagram. The order agent (OA) manages the orders placed by customers via a cloud web application. The product agent (PA) represents a smart product, i.e., a pallet with a working piece at the warehouse equipped with an RFID tag that can communicate with other agents through RFID tag reading and writing. The PA records the order specification in its RFID tag and requests services (e.g., transportation, processing, inspection) to other agents until it reaches its final state and is delivered to the customer. The material handling equipment agent (Mhe) is responsible for carrying the smart product along the production line and or placing it in a buffer or working station for processing, such as the AS/RS, circular conveyor, and FANUC robot arm. The machine agent (MA) is responsible for machining, assembly, and inspection, such as the CNC Lathe, CNC Milling, cobot, and 2D machine vision.

An overview of the modeling process for simulation adopted is shown in Fig. 5.8. First, the mini-factory current state was modeled and simulated to identify improvement opportunities and validation. The future state, which comprises the I4.0 components, was then modeled and simulated under different what-if scenarios to analyze system configurations, identify engineering requirements, and estimate operational performance gains. As indicated in Fig. 5.8, different data sources were used to develop the simulation model, including data collected in the living lab, i.e., manufacturing data, machines' documentation, layout, time report from VERICUT CNC simulation, process data, as well as consultation with domain experts and Web of Science (WoS) and Scopus databases.

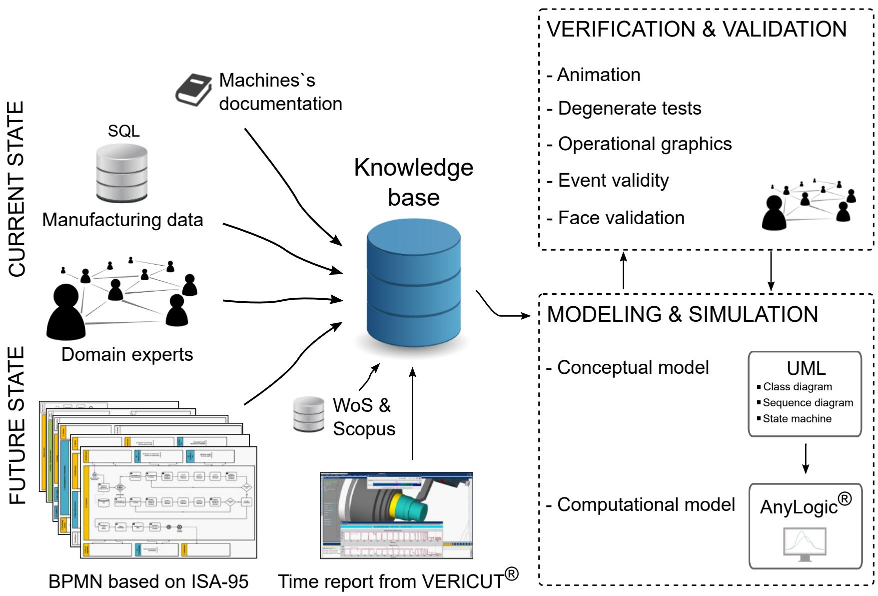


Figure 5.8 Modeling process

The computational model was developed in the multi-paradigm simulation software AnyLogic® (version 8.7.2), following a hybrid simulation (HS) approach that combines DES with ABS to implement the model, where the DES model represents the process flow and ABS the hybrid agents. An overview of the simulation model is presented in Fig. 5.9 and Fig. 5.10, respectivelly. Based on the classification framework for HS proposed by Brailsford et al. (2019), the approach adopted in this study is an interaction type of hybridization, where sub-models interact cyclically at runtime. The conceptual and computational model was verified by researchers and validated by six domain experts (e.g., project managers, technicians) working at the CCTT and participating in the project to transform the mini-factory towards I4.0. This approach is referred to in the literature as face validation, an important method for verifying and validating simulation models (Sargent, 2013). Moreover, we used the operational graphics approach to validate the computational model, which considers the dynamical behaviors of performance indicators visually, 2D and 3D animation and performed some degenerated tests, such as increasing the number of pallet carriers in the conveyor that are other forms of verification and validation (Sargent, 2013).

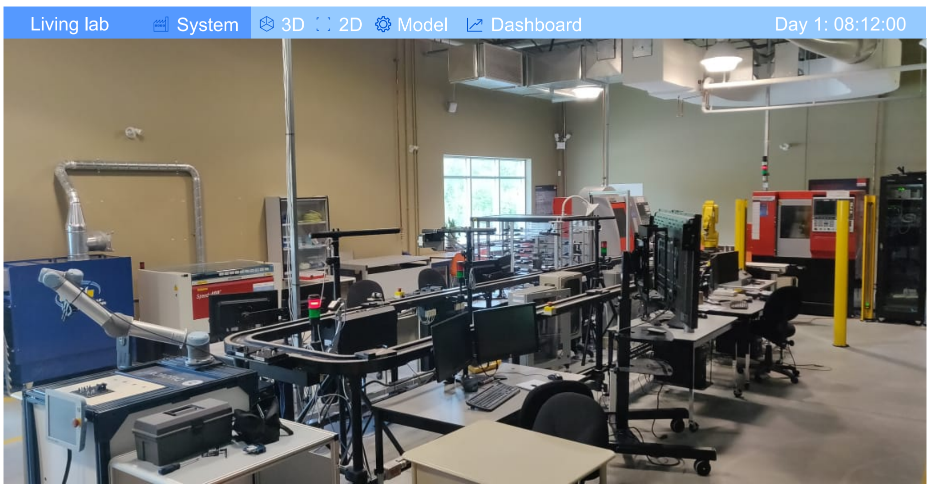


Figure 5.9 Physical system

Figure 5.10 Simulation model developed in AnyLogic® software

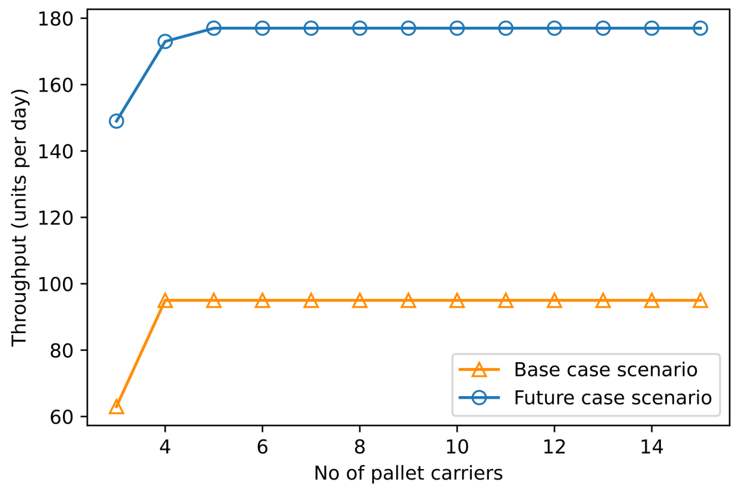
Different simulation scenarios and experiments were developed, including stochastic data and other variables of interest, such as multiple product design. However, this study focuses on presenting the main simulation scenario and experiments used in decision-making since the purpose is to demonstrate the overall approach application. The main simulation experiment defined by subject matter experts for analysis compares the existing system configuration, i.e., a centralized production system in which the CNC machines work in series with a future state scenario in which the CNC machines can work in parallel to execute the tasks published by the smart products. The hypothesis is that smart products would enable using buffer positions at station 2, where the CNC machines are located, resulting in capacity utilization, throughput, and flexibility increase. Table 5.3 summarises the data used to carry out this particular simulation experiment.

First, a sensitivity analysis was performed to identify the number of pallet carriers in the conveyor that maximizes throughput. The results in Fig. 5.11a indicate that the system should operate with at least 5 pallet carriers. Second, a simulation experiment to assess machines utilization was conducted using 8-hours run length terminating simulation. The results presented in Fig. 5.11b supports the hypothesis that the new system configuration enables a significant increase in all machines' utilization and throughput. No peak periods during the day were observed. Moreover, the new system configuration increases the flexibility of the system to deal with high product mix, preventing deadlock, considering that some products variants do not require service form all machines.

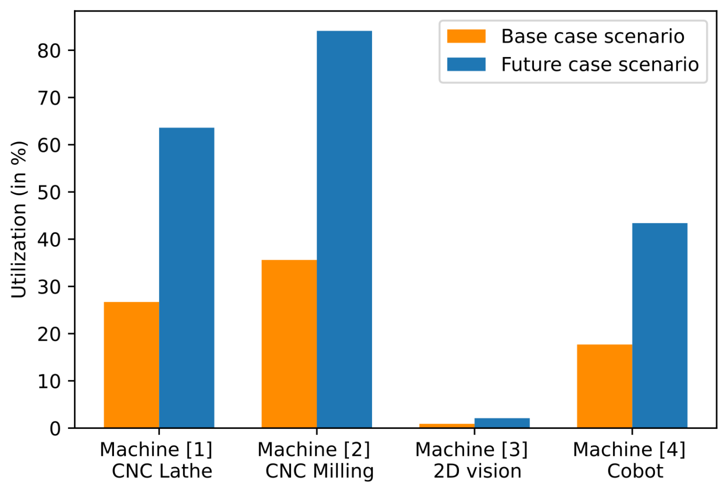
The simulation model contributed to raising fruitful discussions among CCTT members about system configuration, engineering requirements, the relationship between ongoing projects, and strategies for implementing I4.0 scenarios in the mini-factory. These discussions occurred mainly during data collection and meetings animated by the researchers to validate the model. Moreover, the simulation model helped CCTT members better understand their existing system and reach a consensus on future states, considering that the mini-factory does not operate continuously, making it difficult for them to observe certain behaviors. They also indicated an interest in adapting the model to analyze other I4.0 scenarios and experiments to generate data and develop a training and testing platform for artificial intelligence-related ongoing projects. Furthermore, they found the overall approach very useful, suggesting that it can be applied to support manufacturing SMEs' transition towards I4.0, especially during the early stages of I4.0 implementation.

5.6 Discussion and limitations

The study's results indicate three essential elements to implement I4.0 (i.e., maturity model, a roadmap, and a reference architecture), which combined function as a holistic approach to address the development of I4.0 initiatives in SMEs. Furthermore, this study suggests mod-



(a) Throughput rate



(b) Average machines utilization

Figure 5.11 Simulation experiments results

eling and simulation as a cost-effective approach to minimize risks during the development of I4.0 initiatives, which is in accordance with previous findings (de Paula Ferreira et al., 2020; Mourtzis, 2020). It is especially useful for I4.0 scenarios that may require significant financial resources, changes in infrastructure, processes, operations, work organization, or business models by allowing their analysis in a risk-free virtual environment to assist project portfolio selection and planning during I4.0 roadmap development.

Even though the general framework presented in section 5.4 seems trivial, the literature on I4.0 and the digital transformation focuses mainly on applying maturity and/or readiness models and fell short in providing more holistic approaches to support the development of I4.0 initiatives in companies. Furthermore, the existing studies on I4.0 roadmap do not highlight the importance of other elements composing the framework, such as adopting a reference architecture to enable interoperability or using modeling and simulation to support project portfolio planning and analysis during I4.0 roadmap development. Therefore, it may provide companies new insights into the steps and tools to plan their transition towards I4.0.

This study emphasizes the importance of adopting a reference architecture, such as the reference architecture for Industrie 4.0 (RAMI4.0), for implementing I4.0 scenarios and enabling their integration into a company's system as it grows in terms of infrastructure and digital capabilities. Moreover, RAMI4.0 can fulfill the lack of norms and standards related to the implementation of I4.0 concepts point out by several manufacturing SMEs (Lichtblau et al., 2015) by abstracting and linking I4.0 architectural aspects to proven industry standards and providing recommendations of technologies and guidelines for modeling I4.0 systems (Adolphs et al., 2015; Li et al., 2018; Moghaddam et al., 2018).

In contrast to a maturity model, which can easily be applied through an online self-assessment or collaborative assessment with the help of a consulting firm, developing a roadmap may be challenging for SMEs due to a lack of expertise and infrastructure, as described in Lichtblau et al. (2015). In this sense, as described in Section 5.4.1, this study presented a more intuitive technology-based approach to identify I4.0 scenarios that can be implemented based on small-scale projects, that may help SMEs to identify particular areas of their business that could be positively impacted by I4.0 and overcome their lack of clarity and hesitancy in adopting I4.0, as pointed out by Lichtblau et al. (2015) and Moeuf et al. (2018).

The framework for identifying I4.0 scenarios presented in Section 5.4.1 gathers the main concepts of Industry 4.0 (i.e., design principles, technologies) and application areas and performance measures used in industrial engineering and operations management fields, which may help manufacturing SMEs to operationalize I4.0 concept into several I4.0 application scenarios that can be implemented to improve their operational performance. Moreover, the review of several application examples of I4.0 in companies reported in the literature presented in Appendix B may help elucidate the fuzziness of understanding about the term I4.0 through examples of practical applications of I4.0 scenarios in companies and illustrate the application of the proposed framework by establishing a link between I4.0 scenarios and application examples. Furthermore, the cases of I4.0 implementation in Appendix B can serve as a benchmark for companies aiming to implement similar I4.0 scenarios.

In addition to that, the framework for analyzing I4.0 scenarios presented in Section 5.4.2 describes how to model I4.0 scenarios based on RAMI4.0 using agent technology and provides guidelines for developing simulation models of numerous I4.0 scenarios based on a hybrid simulation approach that combines agent-based modeling and simulation with discrete-even simulation, which can be used to support I4.0 roadmap development and the realization of I4.0 initiatives in companies. Alongside digital twin, hybrid simulation is featured as a leading simulation-based approach in the context of I4.0 (de Paula Ferreira et al., 2020). Nevertheless, although modeling and simulation offer great potential to support I4.0, "particularly in SMEs, it is still not standard practice to use model-based simulations in order to configure and optimise manufacturing processes," which represent a significant challenge for I4.0 (Kagermann et al., 2013, p. 43) and may limit the application of part of the proposed framework.

The proof-of-concept case developed at a centre for technological transfer for SMEs in Quebec, Canada, suggests that the overall approach can help SMEs transition to I4.0. Nevertheless, most SMEs will still need technical assistance and be accompanied in their journey to I4.0, especially to apply the RAMI4.0 and their associated standards (e.g., ISA-95), which is complex and time-consuming. Moreover, they need to be encouraged to share their I4.0 initiatives for benchmarking to other companies to create collaborative networks, following the Lean Production practice Yokoten (Paris, 2010) to share information and best practices within and across companies to speed innovation.

Limitations of this study include the fact that the overall framework's application may be subject to contextual factors (e.g., country, company size, sector, resources, organizational culture, policies, regulation) and need to be put into a broader context in manufacturing SMEs, which can be explored in future studies to increase its validity. Other I4.0 scenarios and simulation experiments with more complex behavior could also be explored.

5.7 Conclusion and future research

This study identified and combined essential elements to implement Industry 4.0 (e.g., maturity model, roadmap, reference architecture), proposing a general framework to support companies' transition towards Industry 4.0 in a practical manner. Moreover, this study introduces a new framework to help companies, mainly small and medium-sized enterprises, identify Industry 4.0 scenarios for implementation more intuitively, following a technology-based approach and focussing on small-scale projects to be developed in particular areas of operations management to improve companies' operational performance. Furthermore, this study argues that using a reference architecture, such as RAMI4.0, helps ensure interoperability of the technologies used to implement those Industry 4.0 scenarios and their integration into the system of a company as it grows in terms of infrastructure and the companies increase their digital capabilities. In addition, this study argues that modeling and simulation is an effective approach to support the analysis of Industry 4.0 scenarios for project portfolio selection and planning during Industry 4.0 roadmap development.

The proof-of-concept case developed at a technological transfer centre in Quebec, Canada, suggests that the overall proposed approach is effective and may help SMEs transition to Industry 4.0. Nevertheless, most SMEs will still require technical assistance and accompaniment in their journey to Industry 4.0, especially to comply with RAMI4.0 and their associated standards. Moreover, further research in manufacturing SMEs is needed to explore the proposed framework's potential applications fully. Lastly, future studies may consider using modeling and simulation as a tool to assess the risks, costs, revenue potential, and implementation barriers to help companies' transformation to Industry 4.0.

CHAPTER 6 ARTICLE 3: EXTENDING THE LEAN VALUE STREAM MAPPING TO THE CONTEXT OF INDUSTRY 4.0: AN AGENT-BASED TECHNOLOGY APPROACH

"Passion is the genesis of geniusy"
– Galileo Galilei

This chapter presents a modeling framework to support the development of Industry 4.0 initiatives in manufacturing companies based on the Lean Value Stream Mapping (VSM), complementing the previous contribution. The manuscript contained in this chapter was co-authored[1] with my research director, Prof. Fabiano Armellini, my co-research director, Prof. Luis Antonio de Santa Eulalia, and the partner supervisor, director of research and partnership development, Vincent Thomasset-Laperrière. I am the first author and my contribution is estimated at 90%. The manuscript was submitted to the Journal of Manufacturing Systems on October 13, 2021, and is currently under review as of December 21, 2021.

[1] **Author contributions:** William de Paula Ferreira: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. Fabiano Armellini: Methodology, Supervision, Validation, Funding acquisition, Writing - review & editing. Luis Antonio de Santa-Eulalia: Methodology, Supervision, Validation, Funding acquisition, Writing - review & editing. Vincent Thomasset-Laperrière: Resources, Supervision, Validation, Writing - review & editing.

Extending the lean value stream mapping to the context of Industry 4.0: an agent-based technology approach

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Abstract: With the advancement of the 4th industrial revolution and its enabling technologies, researchers and practitioners discuss the mutual relationships and integration of Lean manufacturing with Industry 4.0 to enhance the manufacturing sector's competitiveness. However, the literature falls short on how Lean principles and practices can support Industry 4.0. To contribute to reducing this research gap, this study explores the integration of the Lean practice Value Stream Mapping (VSM) with hybrid simulation (HS) that combines discrete event and agent-based modeling and simulation. It aims to extend VSM scope to the context of Industry 4.0 to help Industry 4.0 initiatives in manufacturing companies, especially in small and mid-size enterprises (SMEs), wherein managerial approaches are still scarce, enabling it to capture the behavior of more complex entities and distributed production systems. An HS-VSM framework is proposed, and its use is demonstrated through a proof-of-concept case developed in an SME from the furniture and related product manufacturing sector in Quebec, Canada. This study indicates that VSM combined with HS can assist Industry 4.0 roadmap development and help companies understand changes in the material and information flows associated with Industry 4.0 application scenarios.

Keywords: Lean Production, Value Stream Mapping, Industry 4.0, Discrete Event Simulation, Agent Based Modeling and Simulation, AnyLogic®.

6.1 Introduction

Derived from Toyota Production System and popularised by Womack et al. (1990), Lean manufacturing (LM) became a central managerial approach to improve companies' operational performance, e.g., cost, quality, flexibility, and delivery (Shah and Ward, 2003, 2007). It is considered a multidimensional approach that encompasses over 40 management practices, such as value stream mapping, continuous improvement, and leveled production (Shah and Ward, 2003, 2007; Marodin and Saurin, 2013). Furthermore, its implementation has proven to be effective in different companies over different business sectors to increase value-added work by reducing waste throughout value chains (Hallgren and Olhager, 2009; Shah and Ward, 2003; Belekoukias et al., 2014; Shou et al., 2017).

With the advancement of Industry 4.0 (I4.0) and its enabling technologies (e.g., cobots, Internet of Things, big data, artificial intelligence, modeling and simulation), researchers and practitioners from industrial engineering and operations management fields discuss the mutual relationship (e.g., LM supports I4.0, I4.0 supports LM) and integration of LM with I4.0 to enhance companies' competitiveness (Sanders et al., 2016; Buer et al., 2018; Matteo et al., 2019; Rosin et al., 2020; Shahin et al., 2020a; Buer et al., 2021a). A survey conducted with 465 Brazilian companies reveals that the concurrent implementation of LM and I4.0 positively impacts companies‘ operational performance (Tortorella and Fettermann, 2018). Likewise, a survey conducted with 108 European manufacturers suggests that companies aiming to adopt higher levels of I4.0 should concurrently implement LM for superior performance results (Matteo et al., 2019). While there have been numerous studies on how I4.0 can support LM (Sanders et al., 2016; Wagner et al., 2017; Rosin et al., 2020; Shahin et al., 2020b), studies investigating the facilitating effects of LM on I4.0 implementation, such as procedural/prescriptive methods for adopting I4.0 related technologies, are still scarce (Buer et al., 2018; Ciano et al., 2021).

Along the same line, there is still a lack of methods and tools to help companies transition to I4.0, principally for small and medium-sized enterprises - SMEs (Hofmann and Ruesch, 2017; Fettermann et al., 2018; Moeuf et al., 2018; Müller et al., 2018; Wagire et al., 2020). Indeed, several authors suggest that more research is needed to help companies identify areas of their business that could be improved through I4.0 principles and technologies and how they should be implemented to overcome initial barriers, such as the lack of knowledge, infrastructure, and financial resources (Lichtblau et al., 2015; Fettermann et al., 2018; Müller et al., 2018; Stentoft et al., 2020; Wagire et al., 2020; Rosin et al., 2020; Tortorella et al., 2021). In this context, a longitudinal case study conducted in a manufacturing SME reveals that the I4.0 transition process can begin with digitizing certain areas of operation (Ghobakhloo and Fathi, 2020).

In the same direction, de Paula Ferreira et al. (2021) suggest that SMEs should approach the adoption of I4.0 technologies incrementally through small-scale projects developed in pilot areas. Nevertheless, methodologies to help SMEs spot and analyze opportunities for developing I4.0 initiatives are still scarce in the literature.

Value stream mapping (VSM) is the main mapping tool used by the LM community and the first practice to be put in place to deploy LM in companies (Andreadis et al., 2017; Lugert et al., 2018; Shou et al., 2017). It facilitates the systematic identification of waste and supports decision-making for prioritizing and coordinating the development of continuous improvement initiatives by providing a holistic view of the value streams performed to deliver a product or service to customers (James and Jones, 1996; Andreadis et al., 2017). Different approaches to extend VSM to I4.0 have also been proposed. As an example, general guidelines for VSM design integrating I4.0 technologies are provided in Tortorella et al. (2020). In addition, a literature review and empirical survey conducted with 170 Lean experts on the future adequacy of VSM points to modeling and simulation as key technologies to enhance VSM and extend its use to I4.0 context (Lugert et al., 2018). However, non of the existing approaches enables VSM to assess I4.0 production scenarios.

In line with that, limited efforts integrating VSM with hybrid simulation (HS) that combine discrete-event simulation (DES) with agent-based modeling and simulation (ABMS) exist in the literature, and which are considered essential technologies able to capture I4.0 requirements such as modularity, decentralisation, autonomy, flexibility, and agility (de Paula Ferreira et al., 2020). This study aims to extend VSM to the context of I4.0 to support I4.0 initiatives in manufacturing companies by integrating it with HS.

The main contribution of this study is a framework to extend the Lean practice VSM to the context of I4.0, enabling capturing the behavior of complex entities and the dynamic analysis of VSM for more distributed production systems considered in I4.0. It proposes a hybrid simulation-based value stream mapping (HS-VSM) approach that combines VSM with ABMS and DES to support I4.0 initiatives in manufacturing companies, especially SMEs, facilitating the analysis of VSM encompassing I4.0 production scenarios that involve one or more I4.0 design principles and technologies. The framework is tested through a proof-of-concept case conducted in a small-sized manufacturing company in Quebec, Canada.

The remainder of this paper is organized as follows. Section 6.2 provides a background on the related work. Section 6.3 presents the research design. Our modelling framework is described in Section 6.4. Section 6.5 demonstrates the usefulness and ease of use of the framework through a proof-of-concept case. Finally, the main findings of this study, limitations, and avenues for follow-up research are reported in Section 6.6.

6.2 Literature Review

This section first introduces the concept of I4.0 and looks at the application of I4.0 from the perspective of manufacturing SMEs. Then, it highlights the use and importance of modelling and simulation for I4.0 and reviews the literature combining the Lean practice VSM with simulation modelling and exploring its use in the I4.0 context.

6.2.1 Industry 4.0 in SMEs

I4.0 is considered a central strategy to innovate and increase the manufacturing sector's competitiveness in an increasingly digital global economy. It is mainly associated with principles (e.g., flexibility, modularity, interoperability, virtualization, decentralization, autonomy) and technologies, with implications for value creation, business models, work organization, and performance (de Paula Ferreira et al., 2020). It "will lead to the emergence of dynamic, real-time optimized, self-organizing value chains that can be optimized based on criteria such as cost, availability, and resource consumption" (Kagermann et al., 2013, p. 20). There are over 100 definition of I4.0 in the literature, as underlined in Culot et al. (2020), but "technically, Industry 4.0 represents the fusion of IT (Information Technology) and OT (Operational Technology) (Adolph et al., 2020, p. 1).

Examples of IT includes the internet of things (IoT), cyber-physical systems (CPS), cloud computing, big data, and simulation. Examples of OT include supervisory control and data acquisition (SCADA), distributed control system (DCS), programmable logic controllers (PLCs), smart gateways, and smart sensors (Morgan et al., 2021). In line with that, this study takes as a reference the 17 principles of I4.0 described in de Paula Ferreira et al. (2020) and the list of 112 technologies related to I4.0 presented in Gartner (2020), classified by deployment stage, risk, and enterprise value, which can be combined in different I4.0 scenarios for application in companies (Anderl et al., 2016).

SMEs are increasingly interested in transitioning towards I4.0, whether driven by internal motivation or by pressure from customers and or large companies, such as from Original Equipment Manufacturers, fearing being forced out of the market if they do not comply with their requirements (Müller et al., 2018). The empirical survey conducted by Masood and Sonntag (2020) indicates that not just the motivations, challenges, and priorities of SMEs to adopt I4.0 are different compared to large companies, but that SMEs concentrate more on cost reduction and short-term benefits (e.g., flexibility, efficiency). As highlighted in another empirical survey, there are different ways for approaching I4.0, "for many SMEs it is a sum of adaptions, for larger companies it can be a real manufacturing revolution" (Müller et al., 2018,

p. 6). Nevertheless, there is still a lack of I4.0 practice-enhancing research – encompassing the development and assessment of use cases and knowledge-enhancing research – concerning implementation strategies and roadmaps (Schneider, 2018), principally for SMEs, since most "SME oriented tools, frameworks and models do not extend beyond giving a current I4.0 readiness state of an organization" (Masood and Sonntag, 2020, p. 3).

6.2.2 Modeling and Simulation in Industry 4.0

Modelling and simulation are key enabling technologies for I4.0 (Kagermann et al., 2013; de Paula Ferreira et al., 2020; Mourtzis, 2020). They apply throughout the product's entire life cycle (e.g., design, production) and are essential to managing increasingly complex manufacturing systems (Kagermann et al., 2013). The state-of-the-art review on simulation in I4.0 conducted by de Paula Ferreira et al. (2020) describes several simulation-based approaches employed in the context of I4.0, of which hybrid simulation (HS) that combines discrete-event simulation (DES) and agent-based modeling and simulation (ABMS) is one of the main approaches adopted in the literature. This finding is reinforced by the results in dos Santos et al. (2021), which explored the use of HS as an alternative to design digital twin to aid decision-making in production processes and consistent with Jahangirian et al. (2010) and Mourtzis (2020) results, which describes the use of HS to optimize manufacturing systems operations.

It is worth mentioning that agent technology, which encompasses ABMS, is of central importance in the context of I4.0 due to its capability to meet I4.0 requirements (e.g., modularity, decentralization, autonomy) and represent I4.0 components, i.e., an asset plus an administration shell that refers to an asset's data-warehouse, which is considered the basic element for I4.0 systems (DIN SPEC 9134, 2016; de Paula Ferreira et al., 2020; Leitão et al., 2016; Salazar et al., 2019; Fay et al., 2019; Karnouskos et al., 2020; Vogel-Heuser et al., 2020). Therefore, it may have an empowering effect on Lean practices (e.g., VSM), helping overcome some of its limitations in dealing with more complex systems and represent I4.0 production scenarios, which is still unexplored in the literature (Uriarte et al., 2020).

6.2.3 Simulation-based VSM

Lean VSM has been evolving over time, reflecting the need of different business sectors and the ongoing trends of increasingly complex manufacturing systems (Shou et al., 2017; Duggan, 2018). It has been enhanced mainly through simulation modeling technologies (Shou et al., 2017; Uriarte et al., 2020). Table 6.1 presents a list, in chronological order, of key original research articles on simulation-based VSM, including a brief description of the

Table 6.1 Literature on simulation-based VSM

Reference	Main contribution	Simulation method		
		DES	SD	ABMS
McDonald et al. (2002)	Using simulation to enhance VSM	✓		
Abdulmalek and Rajgopal (2007)	Analyzing Lean production and VSM benefits via DES	✓		
Lian and Van Landeghem (2007)	A simulation-based VSM (SimVSM) approach	✓		
Agyapong-Kodua et al. (2009)	Modeling dynamic VSM in aid of process design	✓	✓	
Xie and Peng (2012)	Integrating VSM with ABMS to model human behavior			✓
Helleno et al. (2015)	VSM with DES as a decision-making tool	✓		
Atieh et al. (2016)	VSM with multiple evaluation approaches	✓		
Stadnicka and Litwin (2019)	An extended VSM (VSMap) approach		✓	
Oleghe and Salonitis (2019)	Integrating VSM with SD and DES	✓	✓	
Arndt et al. (2019)	VSM with HS for quality control in manufacturing networks	✓		✓
de Assis et al. (2021)	A practical framework for translating VSM into SD models		✓	
This study	Integrating VSM with HS to support Industry 4.0 initiatives in companies	✓		✓

Legend: DES - Discrete Event Simulation; SD - System Dynamics; ABMS - Agent Based Modeling and Simulation; HS - Hybrid Simulation; VSM - Value Stream Mapping.

studies' main contributions and an analysis of the application of major simulation modeling methods (i.e., DES, SD, ABS, HS) used in industrial engineering and operations management fields (Scheidegger et al., 2018; de Paula Ferreira et al., 2020).

McDonald et al. (2002) are among the first ones to use DES to enhance VSM, addressing its static limitations. Abdulmalek and Rajgopal (2007) followed a case-based approach to demonstrate the application of Lean production to the process sector, using VSM combined with DES to analyze system configurations and Lean performance measures in a large integrated steel mill company. Lian and Van Landeghem (2007) proposed a simulation-based approach (Sim-VSM) that combines object-oriented modeling with a model generator to yield DES models of VSM automatically. Other real cases demonstrating the effectiveness of integrating VSM with DES in different contexts are reported in Helleno et al. (2015) and Atieh et al. (2016).

Agyapong-Kodua et al. (2009) combined VSM with SD modeling and DES to develop a dynamic VSM for experimenting with alternative policies to support process design in complex manufacturing systems with multiple product flows. Similarly, Stadnicka and Litwin (2019) proposed the extended VSM (VSMap), integrating VSM with SD modeling and simulation for manufacturing line modeling and analysis. Oleghe and Salonitis (2019) developed an HS (SD + DES) approach to evaluate the interactions between human factors and process flow elements and assess non-tangible aspects in Lean production systems. de Assis et al. (2021)

introduced a practical framework for translating VSM into SD models based on two leading SD modeling tools available on the market.

Xie and Peng (2012) integrated VSM with ABMS to model human behavior in healthcare environments to improve a hospital operating room's decision-making and operations to minimize patient waiting time and maximize resource utilization. Arndt et al. (2019) proposed an integrated approach for identifying improvement opportunities in quality strategy and optimizing quality control in international manufacturing networks, extending the quality VSM (QVSM) proposed by Haefner et al. (2014) and combining it with an HS approach. They differ from our study in terms of scope, design, and level of analysis since they focus on quality strategy and international manufacturing networks and neither address I4.0 nor provide a general framework for modeling and simulating VSM in its different levels encompassing I4.0 production scenarios.

The systematic literature review on the combination of Lean practices with simulation conducted by Uriarte et al. (2020) reveals that the main Lean practice combined with simulation is VSM and that the majority of studies combines VSM with a DES approach. They also reveal an increasing trend in integrating VSM with SD and that ABMS and HS approaches are the least explored in the literature. This study contributes to this literature by examining the integration of VSM with HS that combines DES with ABMS to support I4.0 initiatives in companies, where practice-oriented approaches for I4.0 realization are still missing.

6.2.4 VSM in the context of Industry 4.0

Lugert et al. (2018) conducted a systematic literature review and empirical survey with 170 Lean experts (both researchers and practitioners from different industrial sectors) to assess VSM's current status and future development needs. Their findings indicate that the Lean VSM method needs to gain more flexibility to cope with the ongoing digitalization and suggest that VSM can support I4.0 and be enhanced by I4.0 technologies. In line with that, Tortorella et al. (2020) developed general guidelines for VSM design integrating I4.0 technologies. Their results suggest that I4.0 technologies can enhance VSM design and reveal links between VSM design guidelines and I4.0 technologies.

Meudt et al. (2017) introduced the Value Stream Mapping 4.0 (VSM4.0) framework to improve the visualization and analysis of the current state VSM by integrating the VSM with key performance indicators data from different IT-systems, such as Information Logistic Waste and Manufacturing Executing Systems. Their results suggest that VSM4.0 can support value stream analysis in I4.0 environment based on digital information and help define current production processes' information handling and utilization. Hartmann et al. (2018) enhanced

Table 6.2 Literature on Lean VSM in the context of Industry 4.0

Reference	Research method	Main contribution
Lugert et al. (2018)	Literature review and empirical survey	Assesses the future adequacy of VSM for Industry 4.0 context through a literature review and survey with 178 Lean experts.
Tortorella et al. (2020)	Literature evidence and experts' opinion	Presents general guidelines for design VSM integrating Industry 4.0 technologies.
Meudt et al. (2017)	Framework	Introduce the VSM4.0 that integrates VSM with an information-logistic waste system.
Hartmann et al. (2018)	Framework	Improves the VSM4.0 for value stream design.
Busert and Fay (2019)	Framework	Presents an extended VSM for information based improvement of production processes.
Ramadan et al. (2017)	Modeling and simulation	Proposes a real-time manufacturing cost tracking system (RT-MCT) that integrates VSM with RFID technology.
Chen (2017)	Modeling	Elaborates an intelligent VSM-based food traceability cyber-physical system approach.
Huang et al. (2019)	Experimental study	Develops a cyber-physical multi-agent system (CP-MAS) for dynamic VSM.
Lu et al. (2021)	Design science	Presents a digital twin-enabled VSM method for production process redesign and reengineering.
This study	Design science	Introduces a framework that combines VSM with discrete-event and agent-based modeling and simulation to support Industry 4.0 initiatives in manufacturing companies, especially SMEs.

the VSM4.0 procedure to support value stream design (i.e., future state) to help identify production processes' classical and information wastes and design lean value streams, especially in terms of information flows. Similarly, Busert and Fay (2019) proposed a new procedure based on an extended VSM approach that incorporates advanced information flow elements to drive information-based improvements for production and logistics processes considering information flow quality and harmonization.

Ramadan et al. (2017) developed a real-time manufacturing cost-tracking system (RT-MCT) framework that combines a dynamic VSM with RFID technology. Their framework enables identifying redundant costs, estimating the cost of non-value-added activities, and providing a cost-time profile to support decision-making for continuous improvement efforts. Chen (2017) developed an intelligent VSM-based food traceability cyber-physical system (CPS) approach to optimize the performance of food traceability systems, combining VSM with IoT, CPS, enterprise architecture, and EPCglobal via fog computing network. Their results suggest that Lean VSM integrated with IoT-enabled CPS can enhance the collaborative efficiency of agriculture food traceability systems. Huang et al. (2019) developed a cyber-physical multi-agent system (CP-MAS) for dynamic VSM, suggesting that VSM based on CP-MAS can reflect dynamic, non-linear material value flows, common in complex production systems.

Lastly, Lu et al. (2021) presented a digital twin-enabled VSM method for production process' redesign and reengineering.

Table 6.2 summarises the literature on the use of VSM in I4.0, including their research method and main contribution. It is important to note that none of these studies provides a framework or general guidelines on modeling VSM based on agent technology or using VSM combined with HS (ABMS + DES) to support I4.0 initiatives in manufacturing SMEs.

6.3 Methodology

This study adopts the Design Science Research (DSR) methodology, as described in Hevner et al. (2004), to assure practical relevance and scientific rigor in developing the HS-VSM framework. With thousands of citations in different scientific databases (e.g., Web of Science, Scopus, Google Scholar), the DSR has become a well-accepted research paradigm in information systems and engineering domains to aid the development of new artifacts (e.g., systems, applications, algorithms, models, frameworks) that can be applied to "the solution of real-world problems or to enhance organizational efficacy" (Peffers et al., 2018, p. 129).

After defining the research problem from the technical procedures, the research starts with a literature review. Next, the HS-VSM framework is designed. Then, its effectiveness, usefulness, and ease-of-use are evaluated through a proof-of-concept case developed in a manufacturing SME (i.e., with 1 to 99 employees) located in the province of Quebec, Canada, that produces cabinets for the residential, renovation, and commercial sectors. This company was chosen for developing the proof-of-concept case mainly because they are engaged in the transition to I4.0, and they are participating in a governmental program that aims to increase the competitiveness of the Canadian manufacturing sector and just received a grant.

6.4 HS-VSM framework

Fig. 6.1 gives an overview of the model-based VSM approach adopted in this study to support I4.0 initiatives in manufacturing SMEs. The first step is to design the conventional current state VSM, following Rother and Shook (2003) guidelines and, if needed, its extensions such as the multi-method VSM for high-variety product environment with complex and concurrent flows described in Duggan (2018), or the extended VSM for multiple plants or across company described in Jones et al. (2011).

The second step is to model and simulate the current state VSM. For this, a discrete-event agent-based framework for VSM modeling and simulation is proposed in this study, de-

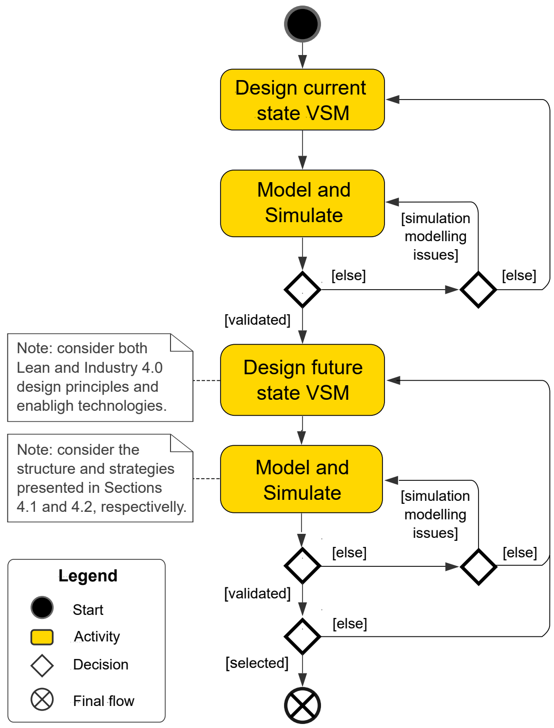

Figure 6.1 Activity diagram of the proposed approach

scribed in the next section. It is important to highlight that the current state VSM, which includes process data (e.g., working time, cycle time, setup time, number of operators), and its corresponding simulation model must be analyzed and validated in conjunction with the company's domain experts. It ensures model validity (e.g., material and information flow, system behavior), project team member engagement, and consensus decision-making.

Next, the future state VSM is designed, modeled, and simulated observing Lean principles, practices, and metrics, as described in Marodin and Saurin (2013), and I4.0 design principles and enabling technologies to generate I4.0 scenarios, as described in de Paula Ferreira et al. (2020) and de Paula Ferreira et al. (2021), aiming to improve companies' operational performance. The use of ABMS in an HS approach enables modeling I4.0 components described in DIN SPEC 9134 (2016) and augmenting the VSM to assess opportunities for digitalization in production processes. This iterative step requires constant exchange between modelers, domain experts, and other stakeholders involved in the I4.0 transformation. The guidelines proposed by Tortorella et al. (2020) to design VSM integrated with I4.0 technologies apply to this stage depending on the I4.0 application scenarios considered. In line with that, the company's I4.0 maturity/readiness assessment results can provide insights for the future state VSM design.

Lastly, the selected future state VSM serves as an input to the I4.0 roadmap development process flow. It is worth mentioning that other simulation-based approaches such as computer-aided technologies and virtual commissioning can be used in later stages of I4.0 roadmap development. They can be used to build planning and explanatory models able to translate the changes proposed in the future state VSM from high to low abstraction levels and technical specifications for implementation in companies (de Paula Ferreira et al., 2020).

A simulation project is usually divided into three phases (Scheidegger et al., 2018). Section 6.4.1 presents a strategy for the conception phase and Section 6.4.2 for the implementation and analysis phases.

6.4.1 Modeling

Lean VSM relies mainly on a set of standardized icons representing different manufacturing and logistics components to mapping value streams for a product family at different magnification levels (Rother and Shook, 2003; Jones et al., 2011). Rother and Shook (2003) describes the conventional Lean VSM at the process and single-plant levels that entail door-to-door material and information flow from receiving to shipping within a facility. Jones et al. (2011) describe the extended VSM that covers multiple plants and across company levels. Based on its characteristics, we can define these icons (building blocks) as software agents for VSM modeling and simulation, enabling capturing complex internal behaviors of entities in distributed systems. An agent is "an autonomous component that represents physical or logical objects in the system, capable to act in order to achieve its goals, and being able to interact with other agents, when it does not possess knowledge and skills to reach alone its objectives" (Leitão, 2009, p. 982). The advantage of integrating ABMS and DES with VSM is that it enables the representation of I4.0 components as described in Salazar et al. (2019) and the dynamic analysis of VSM for complex production systems, including features characterizing I4.0 such as decentralization, modularity, reconfigurability, autonomy, flexibility, and agility (Leitão et al., 2016; Salazar et al., 2019).

This study proposes five types of basic agents (see Fig. 6.2) for modeling and simulating VSM at its different magnification levels: product agent (PA), resource agent (RA), order agent (OA), coordination agent (CA), and facility agent (FA). They can be aggregated and/or specialized and reflect both hierarchical and heterarchical manufacturing systems. The description of its roles, functions, and responsibilities is summarised in Table 6.3. They are based on the product, operational, task, and supervisor holons that form holarchies from the ADAptive holonic COntrol aRchitecture (ADACOR) for distributed manufacturing systems (Leitão and Restivo, 2006), which in turn derive from the holonic manufacturing systems defined in the Product-Resource-Order-Staff (PROSA) reference architecture (Van Brussel

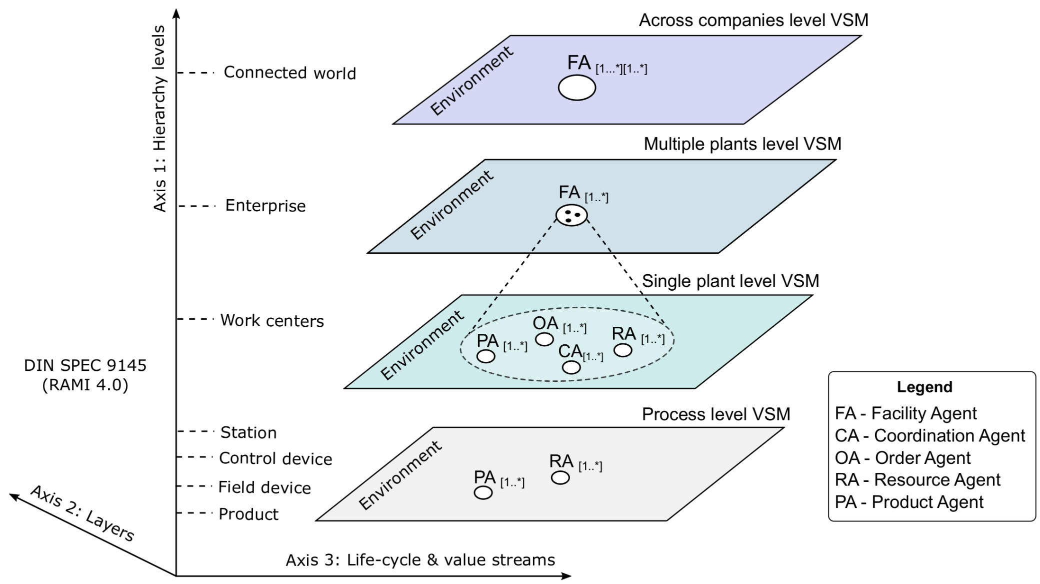

Figure 6.2 Basic agents for modeling VSM at its different magnification levels

Table 6.3 Description of basic agents

Agent type	Description
Product Agents (PA)	They represent the different products and the knowledge to produce them (e.g., product structure, process plan), corresponding to a particular product or product family selected for analysis in a VSM, wherein a data box represents it. They are also responsible for checking if all parts and raw material of a product are available in the system. They can be divided (specialized) into sub-products or components.
Resource Agents (RA)	They represent the different resources presented in a manufacturing or logistics system, providing production capacity and functionality to the other agents, mainly represented by an icon of a process and data box in a VSM. They may also represent human resources, e.g., an operator. Each RA is responsible for deliberating and processing assigned tasks, managing and monitoring machine operations and inventory. They are also responsible for the shipments to customers or between facilities, represented by the plane, train, and truck shipment icons (Jones et al., 2011).
Order Agents (OA)	They coordinate the operations of a particular order, interacting with coordination, product, and resource agents for services to complete the order. It may represent different types of orders, such as customer orders, stock orders, production or work orders, which can be divided or grouped into batches. In the VSM, the OA corresponds to the outside source box icons and production kanban.
Coordination Agent (CA)	It is responsible for coordinating the operations of all orders, handling global tasks of the system, enabling establishing hierarchies and centralized structures in decentralized systems to achieve global production optimization. It is based on the supervisor holon from ADACOR (Leitão and Restivo, 2006), which has self-organization capability, allowing hierarchical and heterarchical control architectures. The CA can also be used to coordinate operations between facilities. In the VSM, the CA covers the functions of the production control, schedule, and Heijunka box icons.
Facility Agent (FA)	It represents the different facilities composing a multi-echelon supply chain network. It represents the factory, cross-dock, and warehouse icons in the extended VSM (Jones et al., 2011). Each FA aggregates PA, RA, OA, and CA, extending the scope beyond shop floor level. At a higher level, a set of FA composes an enterprise.

et al., 1998). It relates to the "structure of LEGO® products, where generic building blocks are provided, enabling the development of any possible construction, without specifying how the future construction should look"(Van Brussel et al., 1999, p. 40).

The correspondence between the hierarchy levels defined in the I4.0 reference architecture RAMI4.0 (DIN SPEC 9134, 2016), and VSM levels are also depicted in Fig. 6.2. It is also possible to specialize the basic agents to meet the requirements of each layer (axes 2) of RAMI4.0 as described in Salazar et al. (2019) and analyze its life cycle. However, it is beyond the scope of this paper that focuses on simulation modeling and manufacturing systems improvement and redesign.

RAMI4.0 is a framework used to logically describe assets and their combination, which compose I4.0 systems, using a level model (DIN SPEC 9134, 2016), while VSM is a framework used to support asset management that refers to "the coordinated activity of an organisation to realize value from assets in the asset life cycle" (van Nierop, 2017, p. 5). Therefore, they can be complementary. Assets in the context of I4.0 are objects of value for an organization, whether tangible or not (i.e., physical or virtual objects) such as a whole manufacturing facility or part of it (DIN SPEC 9134, 2016), represented by the basic agents in our framework to some extent. The hierarchy levels axis of RAMI4.0, which is an extension of ISA-95 hierarchy levels (ANSI, 2010), serves for allocating functional models to particular levels, representing I4.0 environments.The point here "is not implementation, but solely functional assignment"(Adolphs et al., 2015, p.10).

The connected world level (see Fig. 6.2) refers to a collection of enterprises (e.g., manufacturing supply chain network) and relates to VSM across companies level. The enterprise level refers to a collection of facilities (or sites) and relates to VSM at a multiple plants level. The work centers level refers to a logical grouping of resources determined by a facility and relates to VSM at a single plant level. The other levels (i.e., station, control device, field device, and product) serves to realize classifications within a facility and relates to VSM at a process level.

Example cases

The basic agents can be specialized or aggregated to model VSM at its different magnification levels in a way that enables the analysis of several I4.0 scenarios. Fig. 6.3 illustrate four example cases related to I4.0 scenarios using simplified collaboration diagrams. The links with the Lean VSM icons, presented in Rother and Shook (2003) and Jones et al. (2011), is also described next. However, the number of possible configurations and I4.0 examples and application scenarios are countless.

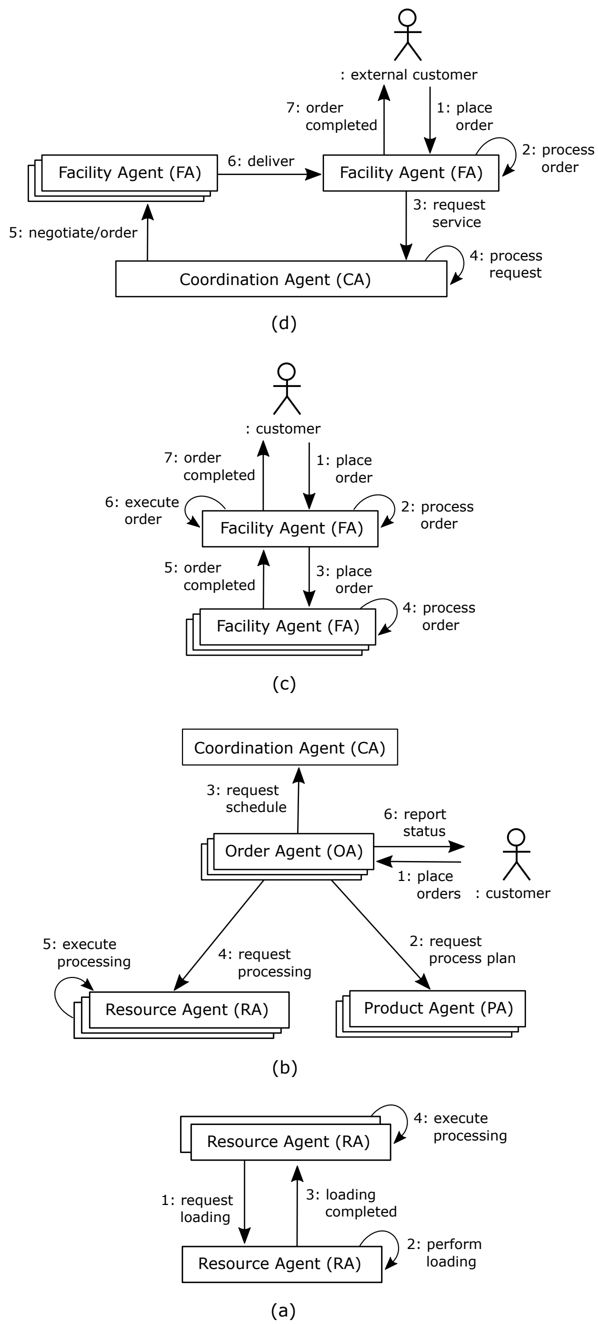

Figure 6.3 Example cases of basic agents' interactions.

Legend: (a) VSM at a process level. (b) VSM at a single plant level. (c) VSM at multiple plants level. (d) VSM across-companies level

Fig. 6.3a presents a model for VSM at a process level. This scenario considers a robotic arm and two CNC cutting machines (i.e., specialized resource agents) grouped into a workstation (aggregated agent), representing a cutting process. After receiving a work order, a CNC cutting machine negotiates with the handling robot for loading or unloading a workpiece. This modeling approach enables the analysis of internal behaviors and dynamics of processes represented by a process and data box icons in the conventional VSM and the analysis of more distributed systems considered in I4.0.

Fig. 6.3b represents a model for the VSM at a single plant level, related to the I4.0 scenario of order-controlled production, as described in Anderl et al. (2016). Once a customer order enters the system, an order agent requests a process plan from the product agents and a schedule from the coordination agent, then requests resource agents processing (e.g., machining, transportation) until it reaches its final state. In a kanban pull system, a coordinator agent can also act for leveling production. Another I4.0 application scenario that can be explored here is operator support in production, and adaptable factory (Anderl et al., 2016) as in reconfigurable and adaptive production systems that can self-organize after a resource added or removed (Kim et al., 2020).

Fig. 6.3c represents a model for the VSM at multiple plants level, such as for a company with two or more production plants (i.e., facility agents) that provide services to each other to fulfil an order. In this case, a facility agent can take either the role of manager (initiator) or contractor, considering the Contract Net Protocol (CNP). In this context, another I4.0 application scenario that can be evaluated is the self-organizing adaptive logistics (Anderl et al., 2016).

Lastly, Fig. 6.3d represents a model for the VSM at across-companies level, such as for the example provided in Jones et al. (2011), which involves suppliers, production plants, cross-dock, and distribution centres from more than one company, represented by facility agents. A coordination agent can be added to prevent a ripple effect or to enable I4.0 scenarios related to crowdsourced manufacturing, acting as a collaboration platform as described in Kádár et al. (2018). Other I4.0 application scenarios that can be investigated in this setting are self-organizing adaptive logistics, transparency, and adaptability of delivered products (Anderl et al., 2016).

6.4.2 Implementation and analysis

In order to provide more practical guidelines for simulation experts and practitioners on the implementation of the HS-VSM approach, this study highlights three main strategies for developing the VSM models (i.e., DES, DES+ABMS, ABMS) as shown in Fig. 6.4. The commercial multi-method simulation modeling platform AnyLogic® was chosen to illustrate the application of these strategies since it “is the most widely utilized tool for building HS models” (Brailsford et al., 2019, p. 730). However, the model-based VSM approach proposed in this study is platform-independent.

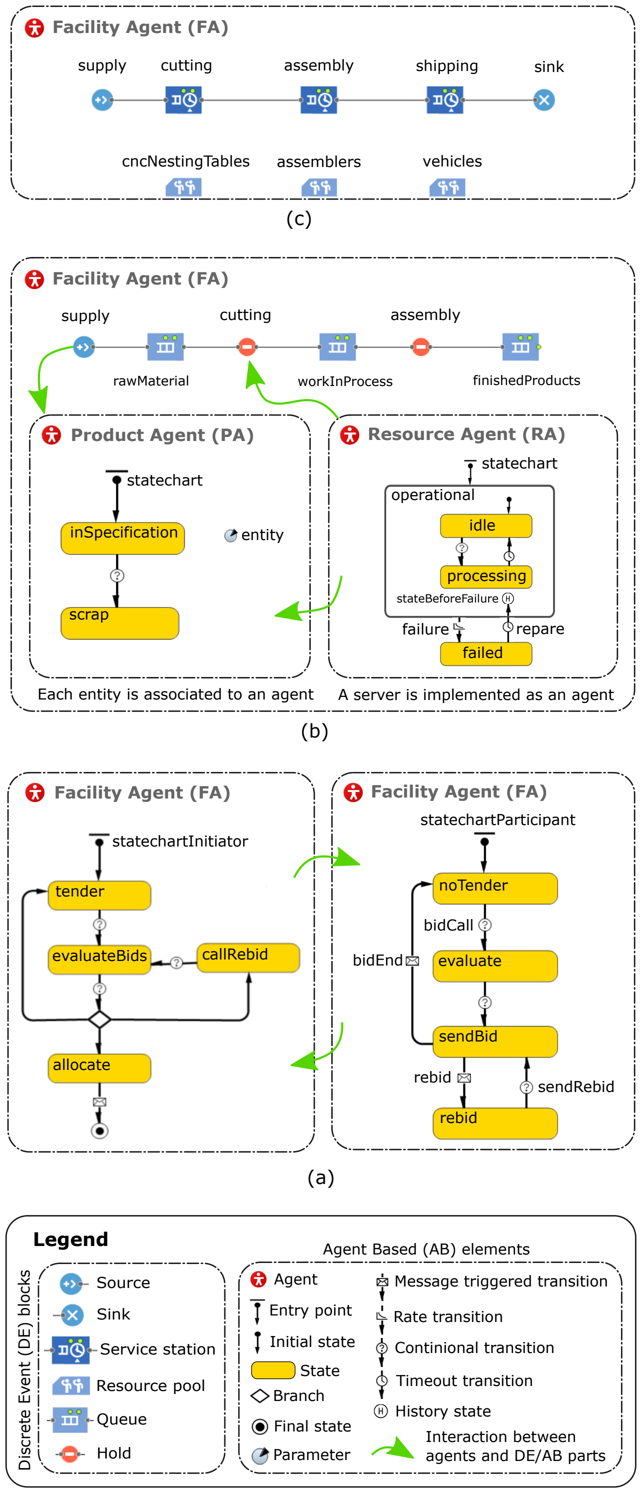

Figure 6.4 Strategies for implementing simulation-based VSM.

Legend: (a) sole ABMS. (b) DES interacting with agent-based model. (c) sole DES or DES inside agents.

Fig. 6.4a shows a sole agent-based model that can be used to simulate VSM at all mapping levels since it follows a bottom-up approach to model complex systems and can easily capture complex material and information flows. However, in the context of this study, its use is mainly suggested for future state VSM once we already have a better understanding of how the existing system is organized. This approach also allows the evaluation of different control architectures, such as hierarchical and heterarchical (Frayret et al., 2004), in which different I4.0 scenarios such as order-controlled production, adaptable factories, and self-organizing adaptive logistics relies on (Anderl et al., 2016).

Fig. 6.4b presents two hybrid strategies that can be used to implement VSM models at any of the four levels, which combine discrete-event and agent-based models, where agents behave and interact using mainly statecharts, events, variables, parameters, and functions. First, each passive entity in the DES model is associated with a product agent to capture individual dynamics that can change the process flow. In this case, each agent points to an entity created in the DES model. When an entity is discharged, the agent linked to it is also deleted from the model. Second, each server station is represented by a resource agent that can capture equipment and process complex behaviors more easily. A resource agent controls the exit of entities from a queue by unblocking the hold object. It can also remove entities from the queue or transfer entities from a flow chart to a statechart and vice versa (Borshchev, 2013).

Fig. 6.4c shows an example of a simplified DES model for a VSM, represented as a process flowchart. Currently, it is the foremost approach adopted in literature to simulate VSM (Uriarte et al., 2020). In this study's context, sole DES models are mainly used to simulate current state VSM at a process or single plant level, depending on the system under analysis. They can also be added inside agents to represent a particular process or the whole process of one or more facilities while analyzing the VSM at multiple plants or across companies levels.

The selection of each strategy will depend on the system under analysis, components complexity, variables of interest, and the type of experiment. In order to provide further insights on the application of the modeling strategies mentioned above to the context of I4.0, some key examples identified in the literature are outlined below.

Examples of studies related to VSM at a process and single factory level that uses only ABMS include Ma et al. (2019), Li et al. (2017a), and Schönemann et al. (2015). Ma et al. (2019) evaluated the flexibility of a hierarchical with a heterarchical manufacturing system, observing the response of the system to unforeseen disruptions related to production job shop scheduling. They adopted a free market architecture as a negotiation mechanism, an extension of the Contract Net Protocol (CNP) with cost factor adaptation. Li et al. (2017a) proposed a self-organized manufacturing system framework with big data feedback assistance to reduce load-unbalancing in manufacturing scheduling and achieve agility and flexibility. They implemented smart products through RFID tags and proposed an intelligent negotiation mechanism, which is also based on the CNP, focussing on the agents' performance to allocate the tasks. Schönemann et al. (2015) proposed a matrix-structured manufacturing systems framework for agile systems configuration, tested through an agent-based simulation model.

In the same context, an example of studies that use an HS approach (as presented in Fig. 6.4b) can be found in Nagadi et al. (2018), which proposed a framework to support the design of smart manufacturing systems linked to an IoT architecture that adopts ABMS to capture the behavior of machines and a DES model to mimic the process flow.

Examples of studies that relate to the VSM model at multiple plants and across companies levels include Xu et al. (2021) and Kádár et al. (2018). Xu et al. (2021) proposed a HS approach to analyze 3D printing technologies adoption to manufacture spare parts for maintenance operations and its impact on operational performance, considering 3D printing facilities located in different network configurations (centralized, decentralized, hub). Their model uses agents to model facilities (top layer), discrete-event elements to model facilities' internal processes (middle layer), and sub-agents to model resources (bottom-up layer), which combines the strategies shown in Fig. 6.4b and Fig. 6.4c. Kádár et al. (2018) proposed a distributed collaboration framework to help the cooperation of various production sites, using ABMS to simulate resource sharing in federated production networks that can dynamically re-configure.

6.5 Proof-of-Concept case

To assess the validity of the proposed framework and illustrate its usefulness and ease-of-use, a real company case was developed in partnership with a college centre for technology transfer (CCTT) that supports manufacturing SMEs in Quebec in their transition toward I4.0. The proof-of-concept case was conducted during 8 weeks in one of the SMEs assisted by the CCTT from the furniture and related product manufacturing sector, NAICS code 337, according to the North American Industry Classification System (NAICS). The company produces cabinets for the residential, renovation, and commercial sectors, following a make-to-order strategy to accommodate customer preferences, and is engaged in the transition to I4.0. The company's identity is protected, and some simplifications were made in the representation of the production processes for the purpose of this article and for maintaining data confidentiality.

6.5.1 Current state VSM

Following the procedure in Fig. 6.1, the first step was to design the current state VSM presented in Fig. 6.5. This VSM focusses on the company's main product family (kitchen cabinets) composed of four types of modules, referred to as modules A, B, C, and D. Customer demand represents 190 modules per day, of which about 11% are modules A, 11% modules B, 67% modules C, and 11% module D. The production process is similar for all modules but with different processing times.

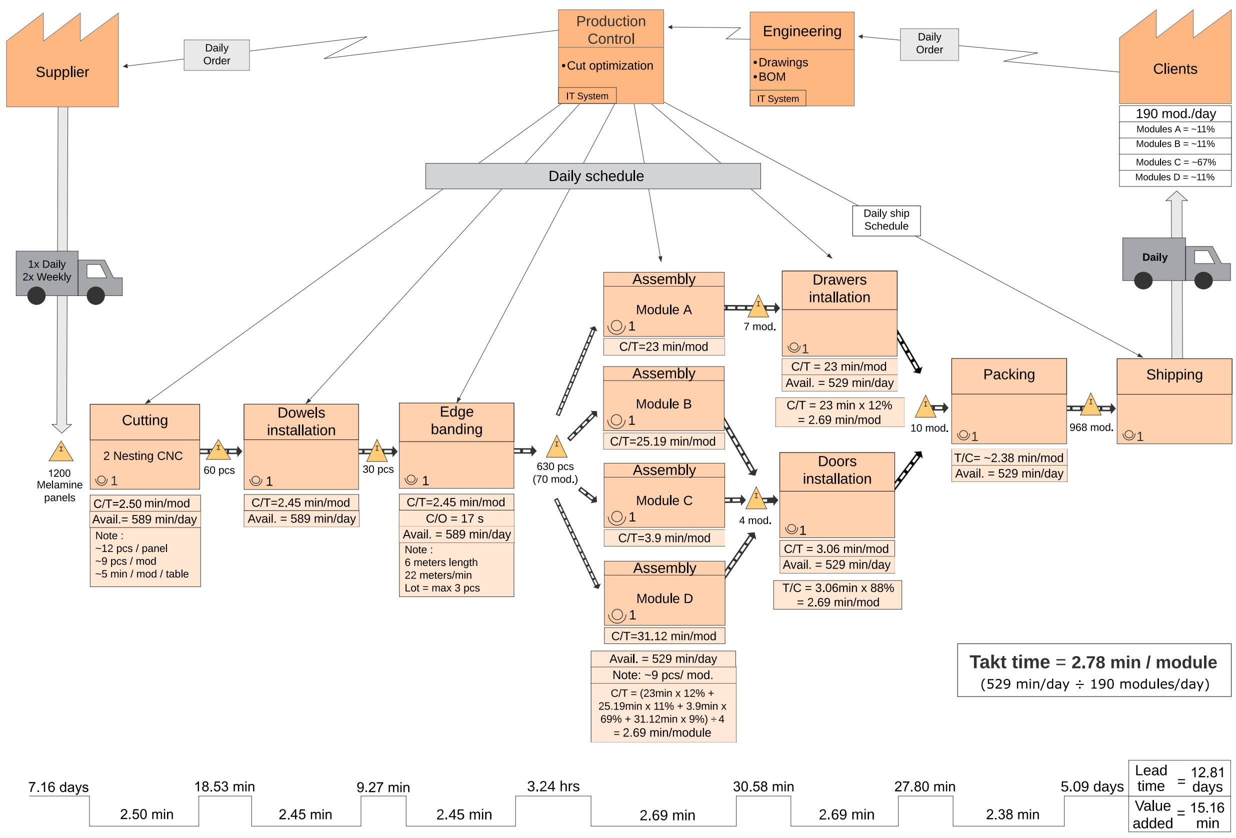

Figure 6.5 Current state map

As shown in Fig. 6.5, the material flow starts with the primary supplied material (melamine panels) being directed to the cutting process, equipped with an overhead crane and two CNC nesting (cutting) tables. Next, the melamine pieces that will compose the modules are identified with a barcode and handled to the wood dowel pins and edge banding processes. Then, they are stocked until all melamine pieces required to assemble a module become available to be manually batched and forwarded to an assembly cell. After that, modules type A go to drawers installation and modules types B, C, and D to doors installation processes. Lastly, the modules are packed and wrapped to avoid any damage during storage or shipping.

The information flow, as depicted in Fig. 6.5, starts with receiving orders from customers. Next, the engineering department translates customer requirements into technical drawings and creates the bill of materials (BOM). Then, purchase orders are sent to suppliers, and the list of cuts is optimized to minimize material waste during the cutting process. Later, production orders are released to the shop floor for execution.

After analyzing the current state map displayed in Fig. 6.5 together with the company's domain expert for waste identification, the following non-value-added activities were observed: (1) high inventory levels of raw material, work in process (WIP), and finished products, compared to work flow, output and customer demand. Even though the company adopts the make-to-order strategy to treat the orders and purchase raw material, the production process operates following a push production approach, accumulating inventory between processes; (2) the cutting process regulates the overall production and represents the actual bottleneck. The fact that the cutting process, dowels installation and edge banding starts before assembly and operates one to two hours overtime every day corroborates this conclusion; (3) excessive material handling, being one of the main causes of scrap and rework.

6.5.2 Future state VSM

The future state map was developed iteratively together with the company's domain experts. The first version followed the system configuration of the I4.0 initiative presented to the CCTT for technical assistance. Essentially, the changes proposed were: (1) replace the edge banding machines with a more modern one; (2) implement an automated storage and retrieval system (AS/RS) in the form of a carousel with a robotic arm for managing inventory before assembly processes, with a storage capacity of about 2000 parts. It would follow a similar solution to the one presented in Crossmuller (2017); (3) automate the assembly of modules type C, adding a pre-assembly process for preparation and removing the protective film from melamine pieces.

After analyzing this future state map and the respective simulation model results, we verified that their initial solution did not match demand. Even after some changes to adjust production capacity, keeping the same concept, no significant improvement in the company operational performance was perceived. It became clear that WIP inventory levels would increase as would the overall production lead time. Therefore, it was suggested to the company that Lean practices and I4.0 principles and technologies should be considered more carefully before going further with the I4.0 initiative. After four iterations, we selected a future state map seen as promising for further analysis as presented in Fig. 6.6.

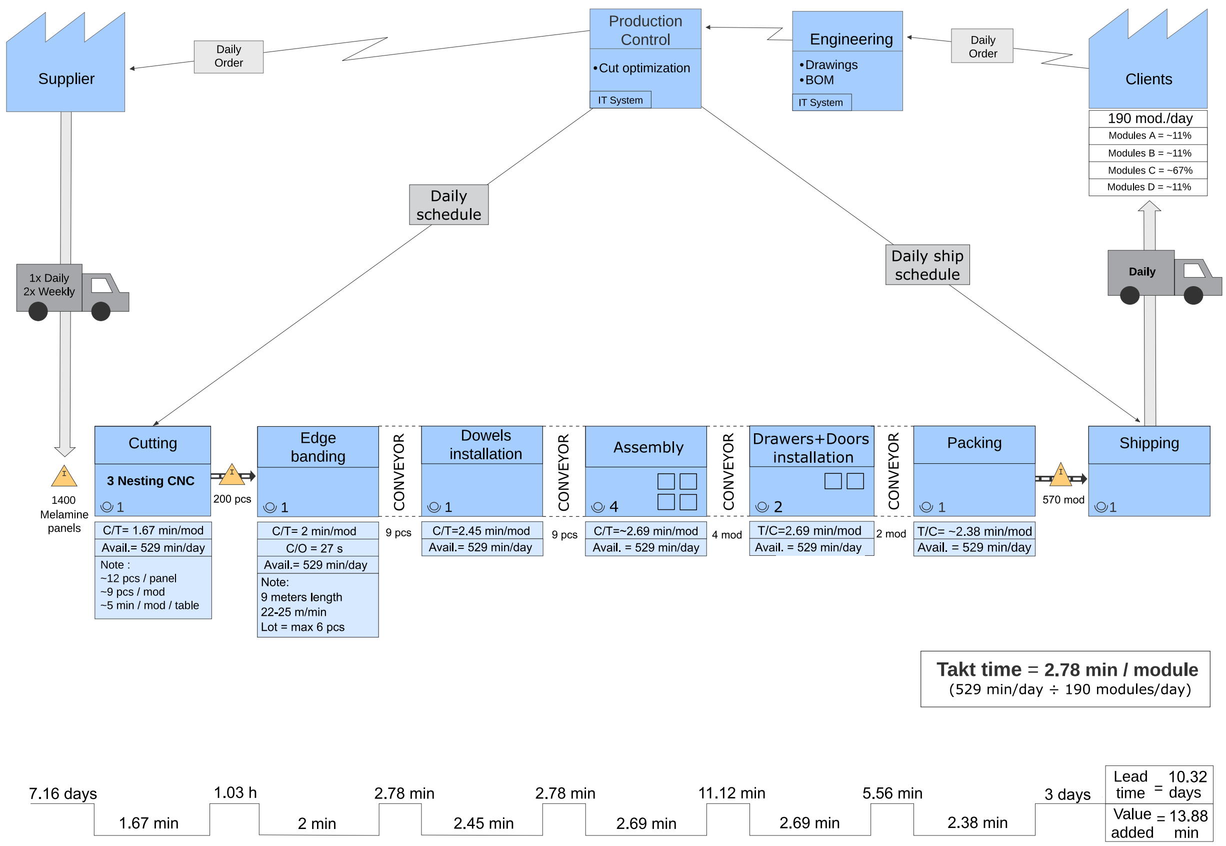

Figure 6.6 Future state map

The changes incorporated in Fig. 6.6 include: (1) install a third CNC nesting table to reduce cutting processing time, allowing batching of the melamine pieces into modules for sequencing in a continuous flow, which prevents the need to accumulate work in process before assembly process; (2) place a linear rack with two robotic arms for storage and sequencing the melamine parts in modules for the subsequent processes; (3) replace the edge machine; (4) install a conveyor system connecting all processes to reduce manual handling that can lead to quality defects; (5) adopt a finished goods inventory policy of a maximum of 3 days of coverage.

These changes comply with the company budget for developing the I4.0 initiative envisioning (in the medium to long term) the I4.0 scenarios of order-controlled production and adaptable factory (Anderl et al., 2016) as the company progresses in its maturity and digital capabilities. It explores I4.0' principles of product personalization, optimization, flexibility, agility, and smart factory mainly through modeling and simulation and industrial automation technologies applied to process engineering manufacturing, production planning and control, and scheduling management areas to improve key performance indicators, i.e., cycle time, lead time, fill rate (de Paula Ferreira et al., 2021). It also pursues the Lean principles of creating a continuous flow and reducing non-adding-value activities. It is important to highlight that using the simulation models was crucial to generate the insights that led to the proposed VSM that contributed to the company reevaluating and improving their project for an I4.0 initiative.

6.5.3 Simulation model

To analyze the future state VSM, a hybrid simulation model was developed following the basic agents described in Section 6.4.1 with the specialization of the resource agents, as presented in Fig. 6.7, which encapsulates the functions of VSM icons and other functions to represent the I4.0 scenario analyzed (e.g., self-regulation). The implementation followed the strategy shown in Fig. 6.4b, described in Section 6.4.2. The model was implemented in the Java-based AnyLogic® software (version 8.7.5), one of the main multi-method general-purpose commercial simulation modeling tools available on the market (de Paula Ferreira et al., 2020; Scheidegger et al., 2018). Experiments were performed on a 9th generation Intel Core i7-9750H laptop with 32 GB of RAM running the Windows 10 operating system.

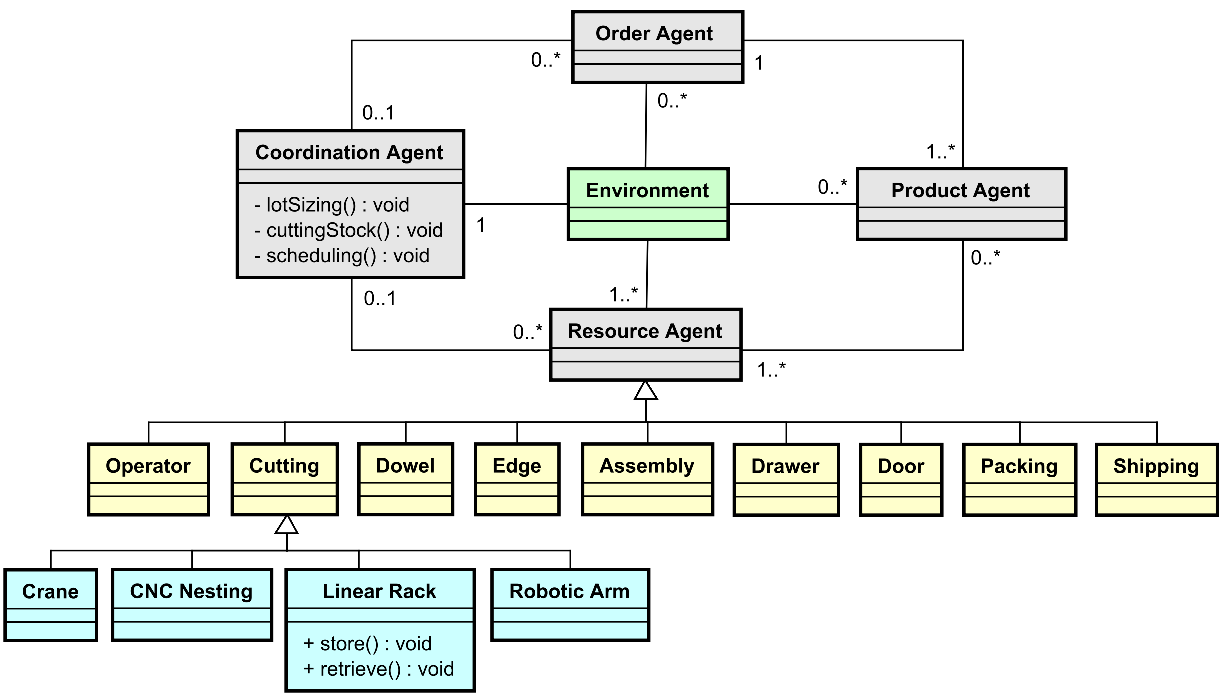

Figure 6.7 Agents in the simulation model

The work-in-process (WIP) inventory levels were one of the main concerns to the company for different reasons (limited space, quality problems, insurance policy). As can be seen in Fig. 6.8, the simulation results show that the WIP levels of the future state are significantly lower compared with the current state. It is mainly possible because, in the future state, we assume that the melamine panels are sequenced to maximize modules formation when cut, and the melamine pieces are batched and sequenced directly after the cutting process. Therefore, in case of unexpected or unplanned events, such as a customer that changes the delivery day after production has started or a part is scrapped and there is no raw material in stock for replacement, the WIP is minimized since we can reschedule the cutting process more flexibly and rapidly before most melamine panels for an order have been cut. It may also reduce the inventory of finished products by improving production planning and control, avoiding anticipating production orders, respecting customers delivery dates. The HS-VSM enabled not just to capture the behavior of the more complex entities (i.e., cutting process, edge process) but also analyze production planning and scheduling under disruptions (e.g., turbulent demand, change in orders, quality problems).

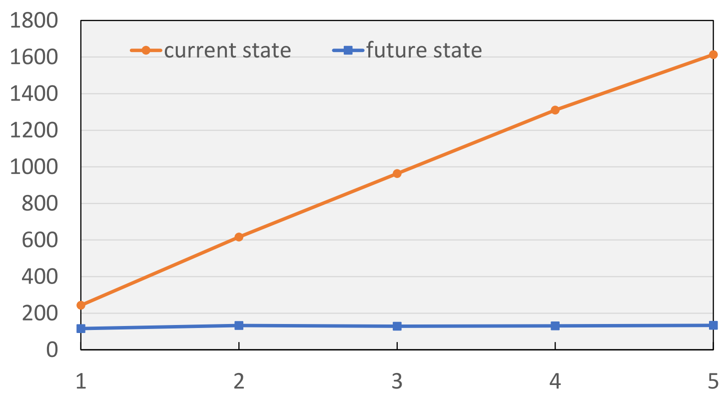

Figure 6.8 Average work-in-process levels in pieces over 5 days

As presented in Table 6.4, the average production lead time is reduced in the future state, involving a process cycle efficiency (PCE) gain of 13.70%, which confirms the potential benefits of the I4.0 initiative. Nevertheless, comparing VAT to LT can be quite shocking, as highlighted in Rother and Shook (2003), the PCE in Table 6.4 shows that the processing time for producing a module will be around 13.88 min, whereas that module will take around 10.32 days to make its way through the production plant until it reaches the customer, indicating that there is lots of room for improvement.

6.5.4 Discussion

The proof-of-concept case illustrated how the proposed framework can be applied to build hybrid simulation-based value stream maps and how they may be used to support I4.0 initiatives in manufacturing SMEs.

Table 6.4 Summary of results

Performance metric	Current state	Future state
Value added time (VAT)	15.16 min	13.88 min
Production lead time (LT)	12.81 days	10.32 days
Process cycle efficiency (VAT/LT)	0.22%	0.25%
Throughput per day	190 mod.	190 mod.

The application of the overall approach lasts for 8 weeks, which fitted the decision time window of the company under analysis. It is worth mentioning that this study was developed in the middle of the COVID-19 pandemic and involved a single modeling and simulation analyst, having influenced the developing time significantly, especially for data collection. Overall, the modeling and simulation efforts based on the I4.0 scenarios selected for analysis and the number of iterations required to design the future state VSM that may also imply simulation model redesign are the main determinants of the developing time.

The fact that Lean VSM is easy to use and is a widespread practice in the industry, as reported in Shou et al. (2017) and Uriarte et al. (2020), helped bring familiarity and engage stakeholders (e.g., managers, IT analysts, operators) in the development of the I4.0 initiative, and may help reduce the learning curve for its application (Glock et al., 2019). Moreover, the use of VSM linked with I4.0 principles facilitated interactions with the company for data collection, modeling, and simulation. Furthermore, it helped the company better understand the I4.0 concept and rethink their I4.0 initiative, putting it into a broader perspective, considering I4.0 scenarios. In the beginning, the company focussed mainly on increasing automation levels in a way that hardware determines the structure and functions are tied to hardware (i.e., Industry 3.0) instead of flexible systems and machines (i.e., I4.0), where functions are distributed through the network, which can cross company boundaries and products can be part of the network (DIN SPEC 9134, 2016). It is a common misconception of I4.0 that may be explained by the lack of a common understanding about I4.0, as discussed in de Paula Ferreira et al. (2020). When LM principles and practices are not implemented before bringing in technologies and digital innovation related to I4.0, there is also the risk that "the results would be just a digitalization of existing wastes" (Ciano et al., 2021, p. 1339). If applied to efficient operations, automation technologies may amplify efficiency, but they may amplify inefficiency if applied to inefficient operations (Buer et al., 2018).

Many of the insights obtained from this study, partially reflected in the future state VSM, would not be possible without modeling and simulation, as identifying the cutting process as the bottleneck, since it was not evident for any of the participants. It became evident only when we started to think about establishing a continuous flow. This result is in accordance with Vanzela et al. (2017), which indicate that the cutting sector represents the bottleneck of most furniture plants. The use of modeling and simulation served not just to refine the VSM and confirm the benefits envisioned in the future state map but also to enrich participation, helping in the reasoning on the potential impacts of the I4.0 initiative on their processes and benefits to operational performance. The use of modeling and simulation complemented the VSM analysis. It supported the analysis that showed that the company's initial project proposal neither matched the demand nor complied with I4.0 principles. Even with certain adjustments, it would not improve the operational performance of the company considerably, reducing their flexibility, agility, and increasing their inventory levels and lead time, having practical implications in the I4.0 initiative, since it was performed before commissioning and contributed to the project that is being implemented.

6.6 Conclusions and future research directions

The mutual relationship of Lean Production and Industry 4.0 is of growing interest and importance both from an academic and a practitioner perspective. Lean principles and practices are seen as prerequisites to implementing Industry 4.0. This study investigated the extensibility of Lean practice Value Stream Mapping (VSM) to support Industry 4.0 initiatives in small and midsize enterprises (SMEs), developed in collaboration with a college centre for technology transfer (CCTT) in Quebec, Canada.

The main contribution of this article is to propose a framework to model and simulate VSM at its different magnification levels (i.e., process, single plant, multiple plants, across companies), enabling evaluating VSM including Lean and Industry 4.0 principles for manufacturing systems redesign and improvement. For this, a hybrid simulation approach that combines discrete-event and agent-based modeling and simulation was adopted. The proposed framework was successfully tested in an industrial case developed in a manufacturing SME from the furniture and related product manufacturing sector, investing 3-5 million dollars in an Industry 4.0 initiative.

This study has some limitations. First, the study's scope was limited to SMEs in the manufacturing sector, and the industrial case focussed on VSM at the single plant level. However, example cases of the configuration of the basic agents for VSM at multiple plants and across-companies level were provided. Second, applying the proposed approach can be seen as time-consuming and expensive depending on a company's decision-making time window, and the levels of investment available for developing an Industry 4.0 initiative since a modeling and simulation analyst has to be involved. Nevertheless, these issues can be remedied by applying the proposed approach through an intermediary whose purpose is to support companies' transition to Industry 4.0 (e.g., CCTT), ensuring that there is enough time for the model results to be useful and that its application cost does not exceed possible savings.

Further research is required to fully explore the potential applications of the proposed framework, including more complex cases. Future research is also needed to examine its generality and validity to other industrial sectors and VSM levels. In addition, the incorporation of artificial intelligence techniques, e.g., applying machine-learning models to process input data for the simulation model or to represent the behavior of Industry 4.0 components in the simulated system, can be explored in future works using the same simulation platform. Moreover, the proposed approach in this study may serve as a basis for developing a software library (build-in blocks) for VSM in the multi-method simulation modeling software AnyLogic®. The application of other software tools can also be investigated.

CHAPTER 7 GENERAL DISCUSSION

"the whole is something beside the parts"
– Aristotle

This chapter presents a general discussion of the research. It is divided into two parts. The first part summarizes the main elements and results of the research, which is mainly composed of three interrelated studies conducted in three major design cycles of artifacts development based on the DSR paradigm. The second part places the results of the research, in terms of the research questions being addressed, into a broader perspective.

7.1 Summary of results

The general objective of this Ph.D. thesis is to enhance the understanding of Industry 4.0 constructs and develop modeling artifacts to support I4.0 initiatives in manufacturing companies, which was divided into three specific objectives, addressed in three complementary studies that had been turned into three original contribution articles. A general overview and relationships between the main elements of this thesis are presented in Fig. 7.1, referring back to the introduction, underlining the main contributions, tying everything together, and providing a perspective of the thesis as a whole.

The first study (Chapter 4) mainly addressed the first specific objective of the research, which was to identify the main constructs of I4.0 and the current state of the art of simulation in I4.0. The results of the first study revealed 17 design principles characterizing I4.0 and 10 simulation-based technologies considered in the context of I4.0, of which hybrid simulation and digital twin were preponderant. It also suggested that simulation-based technologies can capture the design principles of I4.0 and support the investigation of I4.0 from different perspectives (e.g., strategic, tactical, operational), and provided recommendations for future research. This study also presented an analytical framework for modeling and simulation of I4.0 scenarios, which served as a basis for developing the second study.

The second study (Chapter 5) principally addressed the second specific objective of the research, which was to develop a framework for identifying and analyzing I4.0 scenarios. This study showed that the I4.0 concept could be operationalized for production scenarios, which is one of the main focuses of I4.0 (Adolphs et al., 2015), by combining its design principles,

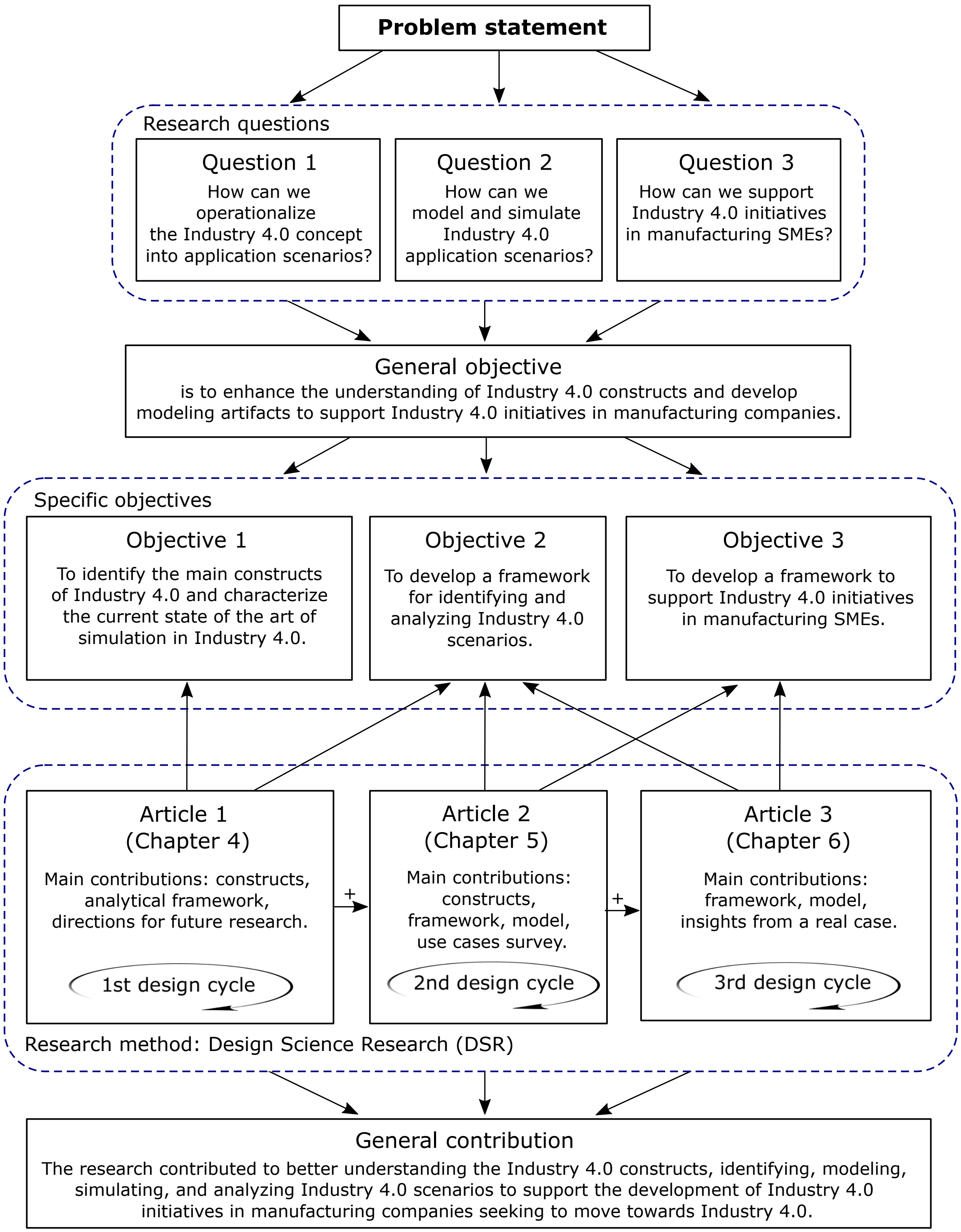

Figure 7.1 Overview and relationship between the main elements of the thesis

enabling technologies, application areas, and potential benefits for operational performance. The proposed framework provided an intuitive way to identify numerous I4.0 scenarios for application, which can be verified related to I4.0 test cases, use cases, or showcases. In addition, this study identified 589 application cases in different online platforms through an I4.0 use cases survey, of which 38 were analyzed relative to generated scenarios to evaluate the proposed framework. Moreover, this study described ways in which I4.0 scenarios can be modeled, simulated, and analyzed. Furthermore, it partially addressed the third specific objective of the research which was to develop a framework to support I4.0 initiatives in manufacturing SMEs by identifying and combining existing I4.0 practices.

The third study (Chapter 6) complemented the previous study by developing a new framework to model and simulate Lean VSM at its different magnification levels, enabling it to capture the behavior of more complex entities and distributed systems related to I4.0 production scenarios. This framework was shown to be useful to support I4.0 initiatives in manufacturing companies, evaluated through a proof-of-concept developed in a manufacturing SME investing in I4.0. Conversely, the framework developed in the second study to identify I4.0 scenarios was adopted in the third study to design the future-state map.

Overall, this Ph.D. thesis identifies a set of constructs and proposes modeling artifacts that can be used to enhance understanding about I4.0 and support the development of I4.0 initiatives in manufacturing companies.

7.2 Implications in a broader context

First, this research suggests that the I4.0 concept can be operationalized into I4.0 scenarios based on its principles, enabling technologies, application areas, and potential benefits to companies' performance. It may help manufacturing companies, especially SMEs, overcome the lack of common understanding of the I4.0 concept and identify I4.0 application scenarios and examples more intuitively, considering that there are over 100 definitions of the I4.0 concept available in the literature, as underlined in Moeuf et al. (2018), and Culot et al. (2020). It may also help SMEs overcome other challenges in adopting I4.0, e.g., general lack of clarity, knowledge resource, and technology awareness limitations (Lichtblau et al., 2015; Müller et al., 2018; Stentoft et al., 2020; Masood and Sonntag, 2020) by facilitating I4.0 roadmap development, which involves defining measures to achieve higher I4.0 readiness/maturity levels, since most "SME oriented tools, frameworks and models do not extend beyond giving a current I4.0 readiness state of an organization" (Masood and Sonntag, 2020, p. 3).

Second, this research indicates that I4.0 scenarios can be modeled and simulated through different approaches (e.g., DES, ABMS, HS) to facilitate the implementation of I4.0 initiatives. This finding reinforces the importance of modeling and simulation in the context of

I4.0 to help companies innovate and improve their performance. It also reinforces the need to "raise awareness of models' potential among the wider engineering community and equip engineers with methods and tools for using appropriate models to depict real-world systems in the virtual world" (Kagermann et al., 2013, p. 43). Having important managerial implications, especially for SMEs, where model-based simulation is still not a common practice. This result is also supported by empirical research (Jeong et al., 2018; Lugert et al., 2018), patent analysis (Han et al., 2018), and other studies in the field (Tao et al., 2018b; Mourtzis, 2020), where modeling and simulation is seen as a means to help promote innovation and improve performance of organizations.

This research also highlights the importance of ABMS in the context of I4.0 as an enabling technology since it can capture I4.0 requirements and represent I4.0 components (DIN SPEC 9134, 2016; Fay et al., 2019). It also provides support for the argument that ABMS "deserves special attention such as new curriculum development" (Macal, 2016, p. 144), having implications for education. Indeed, ABMS applications range across many disciplines and research communities, e.g., engineering, computer science, social science (Frayret, 2011; Macal, 2016; Karnouskos et al., 2020); however, there is still a "lack of ABMS educational programmes for developing the next generation of researchers and facilitating researchers who want to immediately develop ABMS applications" (Macal, 2016, p. 152). The same seems to apply to other simulation-based approaches such as digital twin, which is gaining more and more relevance in the context of I4.0 (Tao et al., 2018b; dos Santos et al., 2021).

Third, this research indicates that I4.0 can be implemented incrementally through small-scale projects developed in pilot areas while companies increase their digital capabilities and maturity. It has important implications especially for SMEs since it may help them to overcome some of their perceived challenges (e.g., lack of expertise, financial resources to make investments, infrastructure) to move towards I4.0 (Müller et al., 2018; Stentoft et al., 2020; Masood and Sonntag, 2020). This argument goes in line with the results of the empirical survey conducted by Masood and Sonntag (2020), which indicate that not just the motivations, challenges, and priorities of SMEs to adopt I4.0 are different compared to large companies, but that SMEs concentrate more on cost reduction and short-term benefits (e.g., flexibility, efficiency). As highlighted in another empirical survey, there are different ways to approach I4.0, "for many SMEs it is a sum of adaptions, for larger companies it can be a real manufacturing revolution" (Müller et al., 2018, p. 6). It is also aligned with the findings of the cross-sectional empirical survey conducted by Buer et al. (2021b) that suggest that SMEs have fewer opportunities to establish large digitalization initiatives and should start with smaller and simpler IT projects.

CHAPTER 8 CONCLUSION AND RECOMMENDATIONS

"We admit knowledge whenever we observe an effective (or adequate) behavior in a given context, i.e., in a realm or domain which we define by a question (explicit or implicit)"
(Maturana and Varela, 1987, p. 174)

This chapter presents the general conclusions of the research. The first section summarizes the main contributions the research. The second section discusses the limitations of this thesis and provides some insights and possible directions for future research.

8.1 Contributions

This Ph.D. thesis took place in the context of a digital economy and I4.0, which are driven by significant advancements and access to information, communication, and automation technologies. It focused on enhancing the understanding of I4.0 and developing strategies to support I4.0 initiatives in manufacturing companies to improve their performance, consisting of a knowledge and practice-enhancing research, multidisciplinary in nature, framed in the intersection of I4.0, M&S, and LM fields, based on the DSR paradigm.

It provides three main significant original contributions. The first contribution consisted in elucidating the I4.0 constructs and the development of simulation-based research in I4.0 through a state-of-the-art review. It was the first study to provide a general overview of simulation-based research in the context of I4.0 and a comparison of simulation technologies and design principles of I4.0. This study was published in a high-impact factor journal in the field of industrial engineering; it has received over 30 citations based on Google Scholar, and was viewed by over 800 researchers based on Research Gate, which are some other aspects that characterize an original and significant contribution (e.g., research that is publishable, cited, and of concern to many people), as described in Lovitts (2007).

The second contribution was to propose a new artifact (i.e., prescriptive framework) by synthesizing and combining theoretical constructs and technologies from different disciplines to put forward new ideas, connections, insights, and perspectives to facilitate identifying and analyzing I4.0 scenarios, encompassing several aspects of the nature of an original contribution in engineering, as described in Lovitts (2007). A proof-of-concept case was developed in a CCTT to evaluate the proposed artifact. It is worth mentioning that a preliminary version of the simulation model presented in this study (named Living Lab), available in the web platform AnyLogic Cloud, received the model of the month award for December 2020 by the simulation software vendor Anylogic®, announced through a newsletter released to users all over the world, suggesting that this study may be relevant to modeling and simulation researchers and practitioners and had a commercial impact, which are some aspects that characterize an original and significant contribution, as discussed in Lovitts (2007).

Likewise, the third contribution consisted in developing a new modeling artifact by combining existing techniques from different disciplines (i.e., I4.0, LM, M&S) in a new way to help modeling and simulation of I4.0 production scenarios to support the development of I4.0 initiatives in manufacturing companies, complementing the previous contribution. It extended Lean VSM scope to the context of I4.0 through a hybrid modeling approach (DES+ABMS), enabling it to capture the behavior of more complex entities and distributed production systems. This artifact was evaluated through a proof-of-concept case developed in an SME from the furniture and related product manufacturing sector in Quebec, Canada, investing in I4.0, providing insights on how LM principles and practices can support I4.0.

Overall, this Ph.D. thesis contributed to advancing the understanding of the I4.0 concept by investigating its principles, application scenarios, and examples of application. It also contributed to advancing knowledge in the modeling and simulation field, of central importance in I4.0 context, by conducting a state-of-the-art review on simulation-based research in I4.0 and by developing artifacts to facilitate modeling and simulation of I4.0 scenarios to support I4.0 initiatives in manufacturing companies, with a focus on SMEs. In addition, it shed light on the enabling effect of LM on I4.0 by extending Lean VSM to the context of I4.0 in manufacturing companies, enabling capturing the behavior of complex entities and the analysis of VSM encompassing I4.0 production scenarios. Moreover, it contributed to practice by providing insights from two cases of I4.0 initiatives in manufacturing companies.

8.2 Limitations and future research directions

Like any other research project, this research has some limitations. First, the proposed artifacts were evaluated through a small number of proof-of-concept cases, limiting their generalizability. More cases are required to enhance and increase the internal and external validity of the proposed artifacts, which may consider different contextual factors (e.g., sector, technology) and I4.0 scenarios. Second, even though different evaluation techniques were adopted (e.g., use cases survey, proofs-of-concept), other techniques such as an empirical survey based on the Technology Acceptance Model (TAM), which is described in Davis (1985), could have been adopted to increase the internal validity of the proposed artifacts. The TAM is widely used to assess the perceived usefulness, perceived ease-of-use, and behavioral intention to use of new artifacts (Masood and Sonntag, 2020).

For that, one may first consider developing an online platform with a toolbox to assist manufacturing SMEs developing I4.0 initiatives, considering that existing platforms are still very limited in scope. It should enable companies to perform I4.0 readiness/maturity self-assessment and competitive benchmark (e.g., by sector, by region); generate I4.0 scenarios and identify example cases, use cases, and showcases; input/share I4.0 case of applications; request technical assistance; discover solutions and services through a recommendation system; and connect with suppliers. It should also facilitate data collection to help the development of policies (e.g., government grants and funding) to foment innovation and technology transfer.

Similarly, the proposed artifacts may serve as a basis for developing a software library for modeling and simulating VSM at its different magnification levels for analyzing I4.0 production scenarios using the multi-method simulation software AnyLogic®. Future works can also explore the integration of simulation modeling with artificial intelligence techniques using the same simulation platform, such as by applying machine-learning models to process input data for the simulation model or to represent the behavior of I4.0 components. Some examples of such integration are provided in Mahdavi and Wolfe-Adam (2019).

In addition, future research may also consider other dimensions and/or aspects of I4.0 that were left out of the scope of this research, such as human aspects and human modeling in I4.0 systems. As discussed in Macal (2016), behavioral modeling still represents a challenge for ABMS. Moreover, according to the fourth edition of OSLO manual (OECD/Eurostat, 2018), there are two main types of innovation firms can make to increase their performance: (1) product innovations[1] that involve substantial changes in goods or services capabilities; and (2) business process innovations[2] that involves six different functions of a firm, divided into core business functions (i.e., producing goods and services) and supporting business functions (i.e., distribution and logistics, marketing and sales, information and communication systems, administration and management, product and business process development). This research focused mainly on I4.0 production scenarios related to business process innovations of firms' core business functions. Future research may explore product innovations and business process innovations of firms' supporting business functions through the I4.0.

[1]Product innovation is defined as "a new or improved good or service that differs significantly from the firm's previous goods or services and that has been introduced on the market" (OECD/Eurostat, 2018, p.70).

[2]Business process innovation is defined as "a new or improved business process for one or more business functions that differs significantly from the firm's previous business processes and that has been brought into use in the firm." (OECD/Eurostat, 2018, p.72).

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APPENDIX A   SIMULATION-BASED STUDIES IN THE CONTEXT OF INDUSTRY 4.0

Reference	Journal	Approach	Empirical nature	Purpose	Application	Principle captured
Ahrens et al. (2018)	ENG COMPUT	VC	RPS	Prescr	Sched	P1,P4,P7,PI,P11,P12,P14
Alqahtani et al. (2019)	INT J PROD ECON	DES	RPS	Pred	Stgy	P11, P12, P15, P16
Benotsmane et al. (2019)	SOCIAL SCIENCES	HS[a]	RPS	Prescr	PrcEMan	P1, P5, P8, P10, P11, P12, P15
Bilberg and Malik (2019)	CIRP ANN MANUF TECHN	DT	HPS	Prescr	AssyLb	P8, P11, P12
Carvajal-Soto et al. (2019)	INT J COMP INTEG M	HS[b]	RPS	Pred	QM	P5, P6, P7, P8, P9, P11, P12, P14
Cecil et al. (2019)	INT J COMP INTEG M	HS[c]	HPS	Prescr	PrcEMan	P1, P2, P3, P4, P5, P7, P8, P9-P12, P14, P16
Charnley et al. (2019)	SUSTAINABILITY	HS[d]	RPS	Pred	QM	P11, P12, P17
Cimino et al. (2019)	COMP IND	DT	LR	N/A	N/A	N/A
Delbrügger et al. (2019)	INT J ADV MANUF TECH	HS[e]	HPS	Pred/Prescr	PrcEMan/PPIC	P1, P5, P7, P8, P9, P10, P11, P12
Dev et al. (2020)	INT J PROD ECON	SD	HPS	Expl	Stgy/PPIC	P1, P4, P5, P6, P7, P8, P9, P11, P12, P14, P17
Ding et al. (2019)	INT J PROD RES	DT	RPS	Pred/Prescr	Sched	P1, P4, P5, P6, P7, P8, P9, P10, P11, P12, P16
Dorigatti et al. (2016)	COMPUT IND	HS[f]	HPS	Pred	SCM	P5, P6, P9, P10, P11, P12, P13, P14
Fantini et al. (2020)	COMPUT IND ENG	N/A	C	N/A	MTE	N/A
Farsi et al. (2019)	SIMUL MODEL PRACT TH	HS[f]	RPS	Pred	PPIC	P5, P6, P9, P10, P11, P12
Frazzon et al. (2018)	INT J PROD RES	HS[g]	HPS	Prescr	Sched/Trans	P9, P10, P11, P12, P13
Fu et al. (2018)	APPL SOFT COMPUT	HS[g]	HPS	Prescr	Sched	P11, P12, P13
Gajsek et al. (2019)	INT J SIMUL MODEL	DES	RPS	Prescr	PrcEMan	P11, P12
Ghadimi et al. (2019)	COMPUT IND ENG	ABMS	HPS	Prescr	SCM	P2, P5, P6, P9, P10, P11, P12, P17
Goodall et al. (2019)	COMPUT IND	DES	RPS	Pred	PPIC	P5, P7, P11, P12, P14
Gorecky et al. (2017)	INT J COMP INTEG M	VR	HPS	Prescr	MTE	P5, P8, P11, P12, P14
Grundstein et al. (2017)	J MANUF SYST	DES	RPS	Proof	Sched	P5, P9, P10, P11, P12, P13
Guizzi et al. (2019)	COMPUT IND ENG	SD	HPS	Pred	Sched/Maint	P11, P12
Guo et al. (2017)	COMPUT IND ENG	PNS	RPS	Prescr	Sched	P1, P2, P4, P5, P7, P8, P9, P11, P12, P17
Havard et al. (2019)	PROD MANUF RES	HS[h]	RPS	Pred/Prescr	PrcEMan	P1, P4, P5, P6, P7, P8, P9, P10, P11, P13, P14
Houston et al. (2017)	SYSTEMS	HS[i]	RPS	Proof	Maint	P1, P5, P6, P7, P8, P9, P10, P11, P12,
Huang et al. (2019)	J MANUF SYST	ABMS	HPS	Prescr	AssLb	P1, P4, P5, P6, P7, P8, P9, P10, P11, P15
Jayasekera and Xu (2019)	INT J ADV MANUF TECH	VR	HPS	Pred	PrcEMan	P5, P11, P12
Kádár et al. (2018)	CIRP ANN MANUF TECHN	HS[f]	HPS	Prescr	CapP	P2, P5, P9, P10, P11, P12, P14
Kaihara et al. (2017)	CIRP ANN MANUF TECHN	HS[f]	HPS	Prescr	CapP	P2, P5, P9, P10, P11, P12, P14
Kumar et al. (2018)	INT J PROD RES	HS[g]	HPS	Prescr	PPIC/Maint	P11, P12
Laurindo et al. (2019)	J COMPUT DES ENG	HS[j]	HPS	Prescr	PrcEMan	P1, P5, P7, P11, P12
Leng et al. (2019)	INT J COMP INTEG M	DT	RPS	Pred/Prescr	PrcEMan	P1, P4, P5, P7, P8, P11, P12, P13

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Table A.1 – *Continued from previous page*

Reference	Journal	SM approach	Empirical nature	Purpose	Application	Principle captured
Liu et al. (2018)	INT J PROD RES	DT	HPS	Pred/Prescr	PrcEMan	P1, P2, P3, P4, P5, P6, P7, P8, P9-P13, P16
Lolli et al. (2018)	PROD PLAN CONTROL	AI	HPS	Pred	InvMgt	P11-P12, P16
Longo et al. (2017)	COMPUT IND ENG	AR	RPS	Disc	MTE	P7, P8, P9, P11, P12
Longo et al. (2019a)	COMPUT IND	HS^k	RPS	Expl/Disc	MTE	P5, P7, P8, P9, P11, P12, P14, P17
Longo et al. (2019b)	COMPUT IND ENG	HS^f	HPS	Prescr	SCM	P2, P5, P9, P11, P12, P13
Mourtzis (2019)	INT J PROD RES	N/A	LR	N/A	N/A	N/A
Nagadi et al. (2018)	INT J COMP INTEG M	HS^f	RPS	Pred	PPIC	P1, P4, P5, P6, P7, P8, P9, P10, P11, P12, P16
Nikolakis et al. (2018)	INT J COMP INTEG M	DT	HPS	Prescr	PrcEMan	P1, P4, P5, P7, P8, P11, P12
Olvera and Vargas (2019)	SUSTAINABILITY	SD	HPS	Pred	Stgy	P11, P12, P13, P16, P17
Park et al. (2019)	INT J COMP INTEG M	DT	HPS	Pred/Prescr	PrcEMan	P1, P2, P4, P5, P6, P7-P9, P11, P12, P14, P16
Parv et al. (2019)	PROCESSES	ABMS	RPS	Prescr	PrcEMan	P12
Pérez et al. (2019)	COMPUT IND	VR	HPS	Pred/Prescr	MTE/PrcEMan	P1, P5, P7, P8, P9, P11, P12
Putman et al. (2017)	INT J PROD RES	VC	RPS	Proof	PrcEMan	P1, P5, P7, P8, P11, P12, P13
Qu et al. (2017)	INT J PROD RES	SD	HPS	Pred	SCM	P1, P2, P5, P7, P8, P9, P11, P12
Renna (2018)	INT J ADV MANUF TECH	HS^g	HPS	Prescr	PrcEMan	P11, P12
Rodič (2017)	ORGANIZACIJA	DT	LR	N/A	N/A	N/A
Rodrigues et al. (2018)	COMPUT IND	ABMS	HPS	Prescr	PPIC	P1, P5, P7, P8, P9, P10, P11, P12, P13, P14
Román-Ibáñez et al. (2018)	INT J COMP INTEG M	DT	HPS	Pred/Prescr	PrcEMan	P1, P2, P4, P5, P6, P7, P8, P9, P11, P12, P14
Ruiz et al. (2014)	COMPUT IND ENG	ABMS	HPS	Pred/Prescr	PPIC	P1, P4, P5, P6, P7, P9, P10, P11, P12, P13
Saez et al. (2018)	IEEE T AUTOM SCI ENG	HS^g	RPS	Prescr	Maint	P1, P7, P8, P14
Schluse et al. (2018)	IEEE T IND INFORM	DT	RPS	Pred/Prescr	CellM	P1, P4, P5, P7, P8, P9, P10, P11, P12
Schönemann et al. (2015)	J MANUF SYST	HS^f	HPS	Pred/Prescr	PPIC	P5, P9, P10, P11, P12, P13
Shpak et al. (2019)	SOCIAL SCIENCES	AI	HPS	Pred	Stgy	P9, P11, P12
Sierla et al. (2018)	COMPUT IND	DT	HPS	Prescr	PrcEMan	P1, P2, P3, P5, P8, P9, P11, P12-P14, P16
Subramaniyan et al. (2018)	COMPUT IND ENG	AI	RPS	Pred	PPIC/Maint	P1, P5, P7, P11, P12
Tamás (2017)	APPLIED SCIENCES	DES	HPS	Pred/Prescr	PPIC	P11, P12, P13, P16
Tan et al. (2019a)	INT J ADV MANUF TECH	AI	RPS	Pred/Prescr	Sched	P1, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13
Tan et al. (2019b)	MACHINES	DT	HPS	Proof	Maint	P1, P7, P8, P11, P12
Tao et al. (2018b)	IEEE T IND INFORM	DT	LR	N/A	N/A	N/A
Tao et al. (2018a)	INT J ADV MANUF TECH	DT	C	N/A	N/A	N/A
Tao and Zhang (2017)	IEEE ACCESS	DT	C	N/A	N/A	N/A
Tiacci (2020)	SIMUL MODEL PRACT TH	DES	HPS	Pred	Sched	P11, P12
Toquica et al. (2018)	INT J ADV MANUF TECH	DT	HPS	Prescr	PrcEMan	P1, P5, P6, P7, P11, P12, P13
Trebuna et al. (2019)	INT J SIMUL MODEL	DES	RPS	Prescr	PPIC	P11, P12
Turker et al. (2019)	MATHEMATICS	DES	HPS	Pred	Sched	P7, P11, P12, P13
Turner et al. (2016)	IEEE T HUM-MACH SYST	HS^l	LR	N/A	N/A	N/A

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Table A.1 – *Continued from previous page*

Reference	Journal	SM approach	Empirical nature	Purpose	Application	Principle captured
Uva et al. (2017)	INT J ADV MANUF TECH	AR	HPS	Prescr	MTE	P8, P11, P12
Vieira et al. (2018)	COMPUT IND ENG	DES	LR	N/A	N/A	N/A
Vieira et al. (2019b)	SIMUL MODEL PRACT TH	HS[m]	RPS	Pred	SCM	P5, P11, P12, P13
Vieira et al. (2019a)	COMPUT IND ENG	HS[m]	RPS	Pred	SCM	P5, P11, P12, P13
Vieira et al. (2020)	SIMUL MODEL PRACT TH	HS[m]	RPS	Expl	SCM	P5
Wang et al. (2016a)	COMPUTER NETWORKS	ABMS	HPS	Prescr	Sched	P1, P4, P7, P8, P9, P10, P11, P12
Wang et al. (2019)	INT J PROD RES	DT	RPS	Prescr	Sched	P1, P4, P5, P7, P8, P9, P10, P11, P12, P13
Xu et al. (2016)	J SIMUL	HS[g]	HPS	Pred	Sched	P7, P11, P12
Yazdi and Azizi (2019)	SUSTAINABILITY	DES	HPS	Prescr	PrcEMan	P11, P12, P17
Zhang et al. (2017)	IEEE ACCESS	DT	RPS	Pred/Prescr	Sched	P1, P2, P3, P4, P5, P7, P8, P9-P13, P16
Zhou et al. (2019)	INT J PROD RES	DT	RPS	Pred/Prescr	Sched/PrcEMan	P1, P4, P5, P6, P7, P8, P9, P10-P12, P14, P15

Legend: [a]AI-3D CAD; [b]DES-AI; [c]VR-AI; [d]DES-SD; [e]DT-Simulation-Optimization; [f]ABMS-DES; [g]Simulation-Optimization; [h] DT-VR; [i]ABMS-Data Science; [j]DES-3D CAD; [k]VR-DES-ABMS; [l]DES-VR; [m]DES-Big Data;

APPENDIX B INDUSTRY 4.0 APPLICATION SCENARIOS AND EXAMPLES

No	Scenario	Case				
		Description	Company	Size	Location	Reference
1	Explore agility and corporate social responsibility through augmented reality at process engineering manufacturing and quality management to improve non-value-added activities, environment, health and safety.	Use of smart glasses instead of conventional scanner terminals during the picking process to increase efficiency by eliminating time-consuming errors and ergonomics by allowing employees have both hands free through a pick-by-vision solution based on AR.	Volkswagen	Large	Germany	Plattform-I4.0 (2020)
2	Explore autonomy through automated guided vehicles at supply chain management to improve non-value-added activities, productivity, and inventory turnover.	Use of autonomous transport vehicles interlinked with each other and capable to interact with employees to increase productivity by reducing manual transport expenses and stock.	Bosch	Large	Germany	Plattform-I4.0 (2020)
3	Explore interoperability, vertical and horizontal integration through semantic technologies at product and service design to improve information sharing.	Develop machines with flexible data exchange (e.g., manufacturer-independent, open data interfaces) based on OPC-UA technology that can be easily integrated vertically and horizontally into customer networks to increase data and information transparency as well as to create new business models (e.g., leasing of machines).	Mosca GmbH	Large	Germany	Plattform-I4.0 (2020)
4	Explore real-time capability through the internet of things, big data and cloud computing at process engineering manufacturing to improve OEE and productivity.	Implementation of a real-time performance management system to increase transparency and improve operational performance (e.g., work productivity, OEE, value-added time).	Schneider Electric SE	Large	France	Robert et al. (2020)
5	Embrace service orientation through the internet of services on transportation management to increase return on sales.	Embedded IoT sensors inside tires to offer new services and increase revenue by helping truck fleet drivers reduce fuel consumption and truck fleet managers to pay for tires based on kilometer-driven bases, moving from industrial to product-service company.	Michelin	Large	France	Daugherty et al. (2015)
6	Explore flexibility and agility through big data, modelling and simulation at supply chain management to improve lead time and fill rate.	Combining big data and simulation modelling to analyse and minimize supply chain disruption risks.	Bosch Car Multimedia	Large	Portugal	Vieira et al. (2019a)
7	Explore virtualization through modelling and simulation at maintenance management to improve information sharing and response time.	Using Digital Twin for planning, operations and maintenance of a power system to improve decision-making response time.	Siemens AG	Large	Finland	Tao et al. (2018a)

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Table B.1 – *Continued from previous page*

No	Scenario	Case				
		Description	Company	Size	Location	Reference
8	Explore real-time capabilities and virtualisation through modelling and simulation at production planning and control to improve information sharing, response time, and inventory turnover.	Use Digital Twin to provide a comprehensive real-time view of factory performance to identify improvement opportunities and enhance response time, on-time delivery, and material flow.	Baker Hughes	Large	USA	Gesing and Kuckelhaus (2019)
9	Exploring virtualisation through virtual reality at training and education management to improve environment, health and safety and compliance to regulations.	Development of a virtual reality based system for emergency response training in industrial sites to reduce environmental risks.	Buncefield	Large	UK	Longo et al. (2019a)
10	Exploring real-time capabilities through the internet of things, cloud computing and artificial intelligence at process engineering manufacturing and transportation management to improve OEE and unit cost.	Implementation of real-time monitoring of assets to improve OEE, reduce transformation costs and increase competitiveness.	Re Alloys steel	Large	Poland	Miśkiewicz and Wolniak (2020)
11	Explore virtualisation through blockchain at supply chain management to improve information sharing and leadtime.	Development of a supply chain platform based on blockchain technology used by key players in the global container shipping industry to enable trusted exchange of information and information transparency (e.g., tracking shipping containers, documentation), which contribute to reducing lead time and transportation costs.	TradeLens (Maersk/IBM)	Large	Denmark	Jensen et al. (2019)
12	Explore service orientation through the internet of things at maintenance management to increase return on asset and return on sales.	Using IoT to incorporate new digital services into predigital products to increase revenue, monitoring aircraft parts, components and systems to offer aircraft engine preventive maintenance and intelligent aircraft fleet optimization services.	GE Taleris	Medium	USA	Daugherty et al. (2015)
13	Explore real-time capability through IoT, big data, and artificial intelligence at maintenance management and quality management to improve response time.	Developed a system to collect over 2 billion data points daily in real-time from around five thousand equipment's using IoT and applied Artificial Intelligence (i.e., machine learning and deep learning) to analysing the collected big data to improve semiconductor manufacturing processes through inspection image analysis and product yield monitoring.	Toshiba	Large	Japan	RRI (2020)

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Table B.1 – *Continued from previous page*

No	Scenario	Case				
		Description	Company	Size	Location	Reference
14	Explore interoperability through semantic technologies at process engineering manufacturing and supply chain management to improve information sharing.	Ensure the interoperability of their different digital platforms and IT-systems such as manufacturing execution system (MES), warehouse management system (WMS), enterprise resource planning (ERP), marketing, and B2B online commerce to improve information transparency.	ADFAST	Medium	Canada	cri
15	Explore real-time capability and virtualization through the internet of things at inventory management, workforce planning, and quality management to improve information sharing, response time, NVAA, capacity utilization, OEE, and throughput.	Using IoT technology to monitor production lines, inventory, and updates on quality in real-time to improve information transparency (i.e., visibility and traceability) to drive faster decision making, addressing bottlenecks in material flow, quality problems, and labor inefficiencies. A 24% increase in OEE, a 10% increase in labor utilization efficiency, a 16% decrease in defects per million opportunities, a 10% decrease in inventory holding cost, and a 10% increase in throughput are reported.	Stanley Black and Decker	Large	Mexico	CISCO (2020), Fettermann et al. (2018)
16	Explore optimization through artificial intelligence at forecast management to improve inventory turnover and order lead time.	Use artificial intelligence to optimize procurement quantity to increase cash flow by decreasing inventory rotation days while preventing material shortages, ensuring on-time procurement of materials to enable order lead time promise of a minimum of 4 business days. A 60% decrease in demand forecasting margin error and a 50% improvement in inventory are reported.	NEC	Medium	Japan	RRI (2020), Fettermann et al. (2018)
17	Explore decentralization and agility through additive manufacturing at product and service design to improve lead time.	Provide 3D printing services based on crowdsourcing and micro-factories, combining open-innovation, rapid-prototyping, and small-batch manufacturing to reduce product and technology development lead time.	GE Fuse	Medium	USA	Weking et al. (2020)
18	Explore decentralization and product personalization through additive manufacturing at product and services design to improve unit cost and order lead time.	Provide 3D printing services through a full-service platform where designers can upload their 3D design (e.g., geometry, material) and sell the product through an online shop. The products are built on-demand using local micro-factories and deliver it to final customers.	Shapeways	Medium	USA	Weking et al. (2020)
19	Explore smart products and service orientation through the internet of service at maintenance management to improve return on sales.	The company sells industrial cranes with remote monitoring to offer predictive maintenance services for a monthly fee.	Konecranes	Large	Finland	Weking et al. (2020)

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Table B.1 – *Continued from previous page*

No	Scenario	Case				
		Description	Company	Size	Location	Reference
20	Explore service orientation through cyber-physical systems (CPS) at purchase management and inventory management to improve inventory turnover.	The company provides CPS® KANBAN full-service based on Kanban systems and principles to help customers make their warehouse and production more effective and transparent by increasing traceability and automating the replenishment and procurement process.	Würth Industrie Service	Large	Germany	Weking et al. (2020)
21	Explore optimization through the Internet of Things at process engineering manufacturing to improve return on asset, environment, health and safety.	The company provides intelligent IoT-based energy-efficiency solutions based on activity-based lighting to customised workplace, adapting the light to employee based on their location and activity being executed.	Zumtobel	Large	Austria	Weking et al. (2020)
22	Explore flexibility, agility, and optimization through artificial intelligence at process engineering manufacturing, capacity planning, and workforce planning to improve cycle time, OEE, and capacity utilization.	Use smartwatches and artificial intelligence for smart value stream management, enabling calculating and adjusting capacity and cycle time dynamically to optimize material flow and worker efficiency.	Baxter	Large	Germany	Plattform-I4.0 (2020)
23	Explore end-to-end engineering integration through cloud computing, additive manufacturing, and cybersecurity at product and service design to improve information sharing.	The company provides a full-service 3D printing cloud-based platform using robust data management and top-level encryption to keep users' data safe.	Kabuku Inc	Medium	Japan	RRI (2020)
24	Explore descentralization and autonomy through drones at transportation management to improve leadtime and response time.	The company provides parcel delivery services to remote and or hard-to-reach areas by air using autonomous drones (i.e., flying postman).	DHL	Large	Germany	DHL (2020)
25	Explore real-time capability, decentralization, flexibility, and agility through the internet of people at inventory and transportation management to improve information sharing, response time, resource utilization, environment, health, and safety.	The company provides a full-service platform and app for humanitarian logistics, supporting transport coordination of aid agencies for freight-pooling and information transparency in the logistics chain to make relief aids reach the people in need more effectively.	Katkin	Medium	UK	Plattform-I4.0 (2020)
26	Explore modularity and product customization through automation and cobot at process engineering manufacturing to improve changeover time, productivity, and response time.	Use product modularity to reach a lot size of one, enabling end customers to customize design and order skis through an online platform (custom shop), which is then produced in a local highly automated factory and delivered directly to the customers.	Atomic	Large	Austria	Weking et al. (2020)

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Table B.1 – *Continued from previous page*

No	Scenario	Case				
		Description	Company	Size	Location	Reference
27	Explore modularity through automation and cobot at process engineering manufacturing to improve changeover time, capacity utilization, and response time.	Employed a modular production line following the plug & produce concept where process modules can be exchanged to enable the production of small batch sizes (i.e., high produce variance) and to optimize setup time and resource utilization.	Phoenix contact	Large	Germany	Plattform-I4.0 (2020)
28	Explore flexibility and agility through automation and cobot at process engineering manufacturing to improve changeover time.	Adoption of new technologies (i.e., programmable welding robot, software tools) to reduce programming time and make the production process more flexible, enabling the manufacturing of smaller lot sizes to respond to a high demand diversification degree.	Radiatole	Small	France	AIF (2020)
29	Explore vertical integration through automation and cobot at process engineering manufacturing and scheduling to improve changeover time and non-value-added activities.	Developed a consolidated line controller named integrated line network box (iLNB) to monitor and control machines to perform automatic changeover based on the host system's production schedule, increasing the assembly systems' flexibility to cope with high product mix. A 30% increase in productivity is reported.	Panasonic	Large	Japan	RRI (2020)
30	Explore smart factory through cyber-physical systems, internet of things, automated guide vehicles, artificial intelligence, automation and cobots at process engineering manufacturing, forecast management, production planning and control, scheduling, capacity planning, assembly line balancing, maintenance management, and supply chain management to improve information sharing, capacity utilization, OEE, lead time, inventory turnover, and response time.	The company adopts crowd-sourcing manufacturing to share 4M (Man, Machine, Material, Method) resources between factories and several other advanced manufacturing technologies (e.g., cobot, IoT, AGV, AI) along with a high degree of industrial automation to optimize the production processes, presenting several cases of Industry 4.0 implementation.	Hitachi	Large	Japan	RRI (2020)
31	Explore smart factory and end-to-end engineering integration through cyber-physical systems, automation, and cobot, artificial intelligence at forecast management, process engineering manufacturing, quality management, maintenance management, product and service design to improve productivity, unit cost, and response time.	Developed a new connected smart factory facility that relies on vertical integration, autonomous machines, e-commerce integration, manufacturing collaboration, machine cloud, and several other advanced manufacturing technologies (e.g., cobot, AI) to improve productivity, operating costs, and return on sales. A reduction of order lead time from 21 days to 6 hours is reported.	Harley-Davidson	Large	USA	Kumar (2016), Fettermann et al. (2018)

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Table B.1 – *Continued from previous page*

No	Scenario	Case				
		Description	Company	Size	Location	Reference
32	Explore product personalization and smart product through the internet of things, cloud computing, modelling and simulation, automation and cobot at product and service design, production planning and control, and scheduling management to improve fill rate, productivity, response time, and customer complaints.	Adopt an automatic order processing (i.e., E-Shop) to produce customized punching tools, wherein customers can configure the tool and place the order, automatically generating the CAD files to be transformed in machine programs. Furthermore, the workpieces are uniquely identified, marked with a neutral DataMatrix Code (DMC), storing customer order data from SAP, and communicating with the machines to request services. A 71% reduction of customer complaints, a 240% increase in on-time delivery, a 71% increase in productivity, and a reduction of order lead time from 4 to 1 day are reported.	TRUMPF	Large	Germany	Plattform-I4.0 (2020)
33	Explore service orientation through the internet of service and big data at product and service design to improve return on sales.	Use big data from customer information to improve vehicle fuel efficiency and enhance customer value, identifying critical factors in engines' development and production to improve fuel efficiency.	MAZDA	Large	Japan	RRI (2020)
34	Explore real-time capability through the internet of things at scheduling management to improve non-value-added activities and productivity	The company uses a production schedule system that sends individual work instructions to each worker equipped with a wearable smart device to reduce unnecessary movement.	JTEKT	Large	Japan	RRI (2020)

Legend: small enterprises - 1 to 99 employees; medium enterprises - 100 to 499 employees; large enterprises - 500 or more employees.