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Industry 4.0 and the New Simulation Modelling Paradigm

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Background and Purpose: The aim of this paper is to present the influence of Industry 4.0 on the development of the new simulation modelling paradigm, embodied by the Digital Twin concept, and examine the adoption of the new paradigm via a multiple case study involving real-life R&D cases involving academia and industry.
Design: We introduce the Industry 4.0 paradigm, presents its background, current state of development and its influence on the development of the simulation modelling paradigm. Further, we present the multiple case study methodology and examine several research and development projects involving automated industrial process modelling, presented in recent scientific publications and conclude with lessons learned.
Results: We present the research problems and main results from five individual cases of adoption of the new simulation modelling paradigm. Main lesson learned is that while the new simulation modelling paradigm is being adopted by big companies and SMEs, there are significant differences depending on company size in problems that they face, and the methodologies and technologies they use to overcome the issues.
Conclusion: While the examined cases indicate the acceptance of the new simulation modelling paradigm in the industrial and scientific communities, its adoption in academic environment requires close cooperation with industry partners and diversification of knowledge of researchers in order to build integrated, multi-level models of cyber-physical systems. As shown by the presented cases, lack of tools is not a problem, as the current generation of general purpose simulation modelling tools offers adequate integration options.

Keywords: *simulation and modelling; automated modelling; Industry 4.0; Digital Twin; SME; multiple-case study*

1 Introduction

Simulation modelling is the method of using models of a real or imagined system or a process to better understand or predict the behaviour of the modelled system or process. As an analogue representation, a physical, mathematical or another type of model is constructed. As such, the simulation and modelling is at least as old as the first use of wooden or stone pieces to represent military units in a chess-like game. However, when referring to the history of simulation, we generally refer to the modern era of mathematics-based simulation. The first modern mathematical model and the first documented use of the Monte Carlo method, as it is known today, is generally considered to have originated with the Buffon-Laplace "needle experiment" in 1777. The experiment is to "throw" needles onto a plane with equally spaced parallel lines in order to estimate the value of π (Goldsman, Nance, & Wilson, 2010).

However, the "golden era" of simulation modelling has arrived in the mid-1940s, when two major developments set the stage for the rapid growth of the field of simulation - construction of the first general-purpose electronic computers such as the ENIAC and the work of Stanislaw Ulam, John von Neumann, and others to use the Monte Carlo method on electronic computers in order to solve certain problems in neutron diffusion that arose in the design of the hydrogen bomb (Goldsman, Nance, & Wilson, 2010).

Today, the use of simulation modelling in science and engineering is well established. In engineering, simulation modelling helps reduce costs, shorten development cycles, increase the quality of products and greatly facilitates knowledge management. A great body of scientific and professional body of literature on various aspects of simulation modelling, e.g. system dynamics, cybernetics

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and system theory, is available, from seminal works such as (Forrester, 1961) and (Kljajić, 2002) to newer publications, for example (Law, 2014) and (Borshchev, 2013).

The aim of this paper is to present the developments within the Industry 4.0 and the 4th industrial revolution leading to the new simulation modelling paradigm, embodied by the Digital Twin concept, and verify the adoption of the new simulation modelling paradigm in the industrial and scientific communities via a multiple case study involving real-life cases of the application of Industry 4.0 methods and technologies. The presented cases introduce methodologies and solutions which allow the automation of general purpose / off-the-shelf simulation modelling tools by using ERP/MES (Enterprise Resource Planning, Manufacturing Execution System) data and standards, and the development of Digital Twin based solutions with widely available sensor technologies.

2 Industry 4.0

The »Industry 4.0« term was coined by the German federal government in the context of its High-tech strategy in 2011. It describes the integration of all value-adding business divisions and of the entire value added chain with the aid of digitalisation. In the "factory of the future", information and communication technology (ICT) and automation technology are fully integrated. All subsystems, including R&D as well as sales partners, suppliers, original equipment manufacturers (OEMs) and customers, are networked and consolidated. In other words: all relevant requirements concerning manufacturing and production capacity are already confirmed during product development. The entire process can be holistically considered and managed in real time from the very first step, including seamless quality assurance in production. (KPMG, 2016)

According to KPMG (2016), networking and transparency in manufacturing provide for a paradigm shift from "centralised" to "local" production. Today, manufacturing already works with "embedded systems", which collect and pass on specific data. In the "factory of the future", a central computer coordinates the intelligent networking of all subsystems into a cyber-physical system (CPS), able to work with increasing independence. Through human-machine interfaces, the physical and the virtual worlds nevertheless work closely together: The human operator defines the requirements, while the process management takes place autonomously. The term CPS describes the networking of individual embedded software systems that collect and pass on specific data. A paradigm shift from "centralised" to "local" production thus takes place: a central information system manages intelligent networking while taking into consideration physical factors such as inputting requirements through human-machine interfaces and allows independent process management. The close interaction between the physical and virtual worlds here represents a fundamentally new aspect of the production process. When this is related to production, we talk of cyber-physical production systems (CPPS). Today, the key enabling technologies and development trends in Industry 4.0 include:

- Green IT,
- Big data and analytics,
- Autonomous robots/systems,
- Horizontal and vertical system integration through new standards,
- Cybersecurity,
- Augmented reality,
- The Industrial Internet of Things,
- Additive manufacturing,
- The cloud, and
- Simulation modelling.

The position of SMEs (small and medium-sized enterprises) in Industry 4.0 is of particular concern, as the level of automation in SMEs is typically low and their funds limited. Industry 4.0 presents several challenges and opportunities to SMEs, which account for a significant share of employment and value creation (GTAI, 2016). SMEs stand to benefit from emerging Industry 4.0 networking and integration standards and open standard architectures as many still use older, proprietary systems. This will allow SMEs to drastically reduce production management efforts and respond to market requirements significantly faster. By joining larger networks, SMEs can become temporary production networks with precisely calculated value added contributions. Furthermore, additive manufacturing (3D printing) and flexible machinery allow the production of very small series and personalized products to be produced at unit costs historically only possible in mass production (GTAI, 2016).

2.1 The 4th industrial revolution

According to the visionary work of Schwab (2016), contrary to the previous industrial revolutions, the 4th industrial revolution is evolving at an exponential rather than linear pace and not only changing the 'what' and the 'how' of doing things, but also 'who' we are. We are witnessing profound shifts across all industries, marked by the emergence of new business models (Marolt, Lenart, Maletič, Kljajić Borštnar, & Pucihar, 2016), the disruption of incumbents and the reshaping of production, consumption, transportation and delivery systems. The big upheavals that this revolution brings are the changes in the economies and jobs: by automating processes, certain jobs disappears, but at the same time new jobs are developed, which are better paid, but also require new skills that allow rapid adaptation, entrepreneurship and innovation. The unstoppable shift from simple digitization (the Third Industrial Revolution) to innovation based on combinations of technologies (the Fourth Industrial Revolution) is forcing companies to re-examine the way they do business. With the development and dissemination of technologies for universal connectivity and autonomous, cyber-physical systems, Industry 4.0 is the driving force behind the 4th Industrial revolution.

While Industry 4.0 is originally a German project, and German government and economy are still the driving force behind it. However, we should keep in mind that Industry 4.0 and the 4th industrial revolution are not a German phenomenon, but are global in nature, as horizontal networking in value chain networks is not limited to just one company or country.

2.2 Development trends in Industry 4.0

Highest levels of Industry 4.0 implementation can be seen in Germany and in multinational technology corporations. Companies such as Siemens, General Electric and Mitsubishi already possess a broad portfolio of production and automation solutions. Manufacturing and automation technology developers such as DMG Mori, Wittenstein, Bosch, Rockwell, Omron, Schneider, Stäubli, Yaskawa, Krones, PSI and Software AG already market many technologies and solutions as "Industry 4.0".

But even without specialized vendors, many of the building blocks necessary for the implementation of Industry 4.0 concepts – including the simulation modelling concepts, are already available, e.g. digital and networkable sensors and control elements (actuators), cloud computing, tablets as human-machine interfaces, integrated software solutions and (industrial) communication networks. New Green IT (Baggia, et al., 2016) power saving technologies allow the construction of large, battery powered, sensor networks. A major deficit, however, is the widespread lack of standards. Many aspects of the technology that is used in Industry 4.0 are already in place, but some areas still require internationally binding standards. Industry 4.0 is currently more of a concept than a reality, and certainly not a product or service that you can buy. This is in part due to the imprecise definition of the term "Industry 4.0" and the exaggerated expectations of customers. What is certain, however, is that Industry 4.0 requires products: industry and management software (e.g. CAD, virtual simulation tools, ERP, MES, PLM), processors (e.g. SCADA, DCS, PLC) and devices (e.g. Ethernet, robotics, RFID, motors and drives, relays, switches, sensors) (KPMG, 2016). These devices require specialist expertise in information and communication technology (ICT) and automation technology, which presents both a challenge and an opportunity to the educators and trainers of the future work force.

3 Modern simulation paradigm

In the past few decades, computer simulation has become an indispensable tool for understanding the dynamics of business systems. Many successful businesses intensively use simulation as an instrument for operational and strategic planning. In the modern simulation paradigm (Kljajić, Bernik, & Škraba, 2000), the connectivity of a simulation model typically involves integration with a static database of business variables, a user friendly front-end and additional decision support tools such as expert systems (ES) or group decision support systems (GDSS). The schematic of such a system is shown in Figure 1.

Simulation has been mostly used to develop standalone solutions with a limited scope and lifetime (Harrell & Hicks, 1998). However, the penetration of computer simulation into various areas of business processes has resulted in the need to connect the simulation models used in different parts of an organization (Kljajić, Bernik,

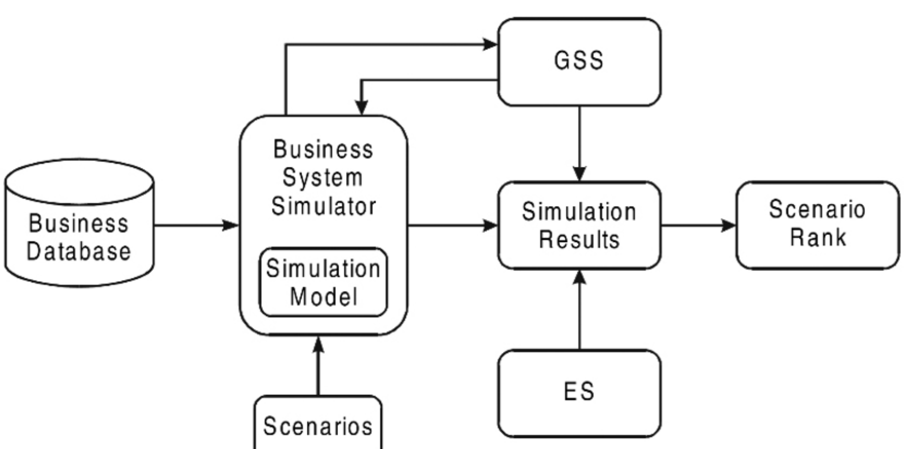

Figure 1: Schematic of a typical simulation modelling based DSS system (Kljajić, Bernik, & Škraba, 2000)

& Škraba, 2000). Also, the trend in simulation development has shifted from purely analytical and optimisation oriented models to integrating simulation models into decision support tools to be used recurrently. For example, by integrating models of various parts of an organization, a joint distributed simulation system can be built to conduct large-scale business system simulations, giving an overview of the modelled organization. This development has brought changes in the requirements for simulation model design. Stand-alone models, accessible only to simulation experts are to be replaced by models that can be connected to various data sources and destinations and controlled or even modified via user-friendly front-ends or other applications (Rodič & Kljajić, 2005).

3.1 The need for a new simulation modelling paradigm

Since the first general engineering applications of in 1960s, simulation modelling has developed from a technology accessible to mathematical and computing experts to a standard tool in an engineer's portfolio, used to solve a range of design and engineering problems. Simulation based decision support tools allow solution development, validation and testing for systems and individual elements of systems, and form the basis of the model-based systems engineering (MBSE) approach.

However, with the increased integration of simulation modelling in the product life cycle management, the user requirements have changed considerably. Increasing product variants and customisable products require more flexible production systems. The advent of the Industry 4.0 paradigm has brought changes to the simulation modelling paradigm as well. The Industry 4.0 paradigm requires modelling of manufacturing and other systems via the virtual factory concept and the use of advanced artificial intelligence (cognitive) for process control, which includes autonomous adjustment to the operation systems (self-organization). The new simulation modelling paradigm is best surmised by the concept of "Digital Twin", which we examine in the following chapters. The concept of Digital Twin extends the use of simulation modelling to all phases of the product life cycle, where the products are first developed and tested in full detail in a virtual environment, and the subsequent phases use the information generated and gathered by the previous product life cycle phases. Combining the real life data with the simulation models from design enables accurate productivity and maintenance predictions based on the realistic data. Table 1 shows the main aspects of the evolving simulation paradigm from 1960s until today.

Due to shortened product development cycles, manufacturers have to move from traditional design processes and practices, that used a "build it and tweak it" approach and must instead take a more systems-design approach that has proven to be an essential part of the design process within the aerospace and automotive industries for many years. Through formal requirements management, and the development of high-fidelity dynamic models used in simulations of the system, manufacturers can validate the design against the requirements in the early stages of the process. The resulting high-fidelity model from this process is typically referred to as the Digital Twin, a concept borrowed from space programs. In space missions, any changes can be fatal, therefore all modifications of a vehicle, probe or rover on a mission, are tested on a detailed simulation model of the system to ensure the change produces the desired effect. (Goossens, 2017)

Currently, automated model development is more common with methods that allow easier and more standardized formal description of models, e.g. Petri nets (Conner, 1990), (Gradišar & Mušič, 2012). Automation of model construction and adaptation can significantly facilitate the development of models of complex systems (Lattner, Bogon, Lorion, & Timm, 2010), (Kannan & Santhi, 2013) and generation of simulation scenarios. Optimisation through modification of model structure can be performed by constructing several versions of the model and input data (i.e. scenarios) and comparing simulation results. To

Table 1: Evolution of simulation modelling paradigm (adapted from (Rosen, von Wichert, Lo, & Bettenhausen, 2015))

Individual application:	**Simulation tools:**	**Simulation-based System Design:**	**Digital Twin Concept:**
Simulation is limited to very specific topics by experts, e.g. mechanics. **1960+**	Simulation is a standard tool to answer specific design and engineering questions, e.g. fluid dynamics. **1985+**	Simulation allows a systemic approach to multi-level and multi-disciplinary systems with enhanced range of applications, e.g. model based systems engineering. **2000+**	Simulation is a core functionality of systems by means of seamless assistance along entire life cycle, e.g. supporting operation and service with direct linkage to operation data. **2015+**

accelerate the development of model versions and scenarios one can construct algorithms that build or modify simulation models according to model input data. This is especially useful in cases of large simulation models and if the model variants are prepared by an algorithm, e.g. an optimisation algorithm. Automated model building and modification however requires that the model structure can be modified with an algorithm without manual interventions. (Rodič & Kanduč, 2015)

These three points summarize the main changes to the simulation and modelling paradigm in the change from stand-alone simulation-based decision support system to the Digital Twin:

- Connectivity and integration in a wider IS (manufacturing or enterprise resource planning (MRP, ERP) is the norm,
- The modelled system is modelled with a holistic, multi-level/resolution approach, which includes physical modelling. Several aspects of the simulation model require a high level of details and low level of abstraction,
- Construction and modification of models is automated (data-based) to the highest degree.

4 The Digital Twin: Digital Master and Digital Shadow

Industry 4.0 envisions interlinked and autonomous manufacturing systems self-organizing the production of small batch sizes down to lot size 1. To realize this vision, new design paradigms in manufacturing system design are necessary. A definition of a Digital Twin, proposed by researchers of Fraunhofer IPK and TU Berlin provides a separation of usage data and models for simulation: "A Digital Twin is the digital representation of a unique asset (product, machine, service, product service system or other intangible asset), that alters its properties, condition and behaviour by means of models, information and data". (Stark, Kind, & Neumeyer, 2017)

Today every instance of an individual product or production system produces a "digital shadow", which is the name for the structured collection of data generated by operation and condition data, process data, etc. Hence an instance of a Digital Twin consists of: Digital Master - a unique instance of the universal model of the asset (machine), its individual Digital Shadow and intelligent linking (algorithm, simulation model, correlation, etc.) of the two elements above (Stark, Kind, & Neumeyer, 2017). This is the foundation of a CPPS.

The simulation and validation of complex CPPS with a high amount of CPS will need abstracted behaviour models of systems and sub-systems to avoid long simulation runs. Digital Twins can ensure reliable simulation results, but the design of Digital Master according to their Digital Shadow must be defined first. With help of holistic behaviour modelling, a simulation model for validation of future usage of CPPS is available: the simulation environment can provide the ‘‘Digital Master’’ of the CPPS with the capability to interlink usage data and sensor values. A ‘‘Digital Twin’’ for evaluation of the interaction of a CPPS within an interlinked, autonomous production and linked capability simulation is possible (Stark, Kind, & Neumeyer, 2017).

An important aspect of the Digital Twin concept is the accumulation of knowledge - the information created in every stage of the product lifecycle is stored and made available to the following development stages. This greatly improves the knowledge management aspect of product development.

A high fidelity simulation models - Digital Twin of a process or part of process has several potential uses in an organization (Goossens, 2017):

- An in-line Digital Twin allows an operator to train on a virtual machine until they have the skills and confidence needed to operate the real machine, without the expense of a dedicated training simulator. Using an in-line Digital Twin accelerates the learning process and minimizes the risk of damage to the machine.
- Using optimal control and model-predictive control techniques, combined with advanced machine-learning capabilities, a Digital Twin can also be used to identify potential issues with its real machine counterpart. A high-fidelity physics model running in parallel with the real machine can immediately indicate a potential malfunction in the real machine by detecting a drift between the machine's performance and the behaviour of the model. The information could be used to stop and service the malfunctioning machine or use the model to provide a strategy for compensating for a decrease in performance without slowing or stopping production.
- An embedded Digital Twin would provide the basis for increasing the self-awareness of the machine, allowing it to optimize its own performance for given duty cycles, diagnose and compensate for non-catastrophic faults, and coordinate operation with other machines with minimal input from the operator.

The Digital Twin is the natural result of adopting a system-design approach to product development and can be readily integrated into the final product for training, in-line diagnostics, and performance optimization and beyond. Most industrial automation platforms support the Functional Mock-up Interface (FMI) as a way of integrating a real-time implementation of the Digital Twin so it can be run in-line with the real machine. By using simulation software, engineers can construct a virtual prototype of the machine design, directly from the CAD representation, and integrate it as a Digital Twin on their real-time platform as a Functional Mockup Unit (FMU). (Goossens, 2017)

According to Goossens (2017), the cost to create dynamic models of multi-disciplinary systems has declined considerably over the past few years with the advent of powerful and easy-to use mathematical systems-modelling tools and general purpose modelling tools such as Maplesim, Matlab and Anylogic. Identifying and addressing design issues early in the design process saves huge costs and associated disruption to the project schedule in late-stage design requests, therefore, the return on the up-front costs for tools and expertise to implement this process is very quickly realized. Manufacturers are beginning to implement rigorous systems-design processes that accommodate the complexities of developing multidisciplinary systems, with high-fidelity virtual prototypes, or Digital Twins, at the core of the development process. An example of a Cyber Physical Production System incorporating simulation modelling via Digital Twin is shown in Figure 2.

In such a systems, the business system simulator contains a Digital Twin model of the business process. The Digital Twin is used to supply the array of decision support tools with a detailed, dynamically update digital representation of the real-life business process (e.g. a manufacturing plant). The process data is gathered real-time by the array of sensors and smart machines in the business process, stored in the business database and then transferred to the Digital Shadow. The Digital Master model's operation is adjusted according to the data in the Digital Shadow, allowing on-line optimization and decision support, and control of the process automation, creating a controlling feedback loop, which is the basis of cybernetic systems (Kljajić, 2002).

5 Methodology

To explore the adoption of the new simulation modelling paradigm based on the Digital Twin concept we have conducted an explorative multiple-case study of simulation modelling oriented research projects implementing the Industry 4.0 paradigm. As the adoption of the Industry 4.0 paradigm is slowest among SMEs (GTAI, 2016), we have selected cases aiming to develop Industry 4.0 approaches and methods feasible for implementation within SMEs.

Case study research, through reports of past studies, allows the exploration and understanding of complex issues and can be considered a robust research method particularly when a holistic, in-depth investigation is required (Zainal, 2007). As noted by (Robson, 1993), a case study is the study of an arbitrary contemporary phenomenon or phenomena, with the researcher/s studying not affecting the study subject. Most case studies are qualitative in their nature (Bengtsson, 1999). Multiple case studies can be used in most situations in preference to single case studies to achieve more robust results (Bengtsson, 1999) and strengthen the findings from the entire study (Yin, 2017). The goal of conducting multiple case studies is analytical generalization, not statistical generalization (Robson, 1993). The multiple cases can be used to represent confirmatory cases (i.e., presumed replications of the same phenomenon), and present value beyond the circumstanc-

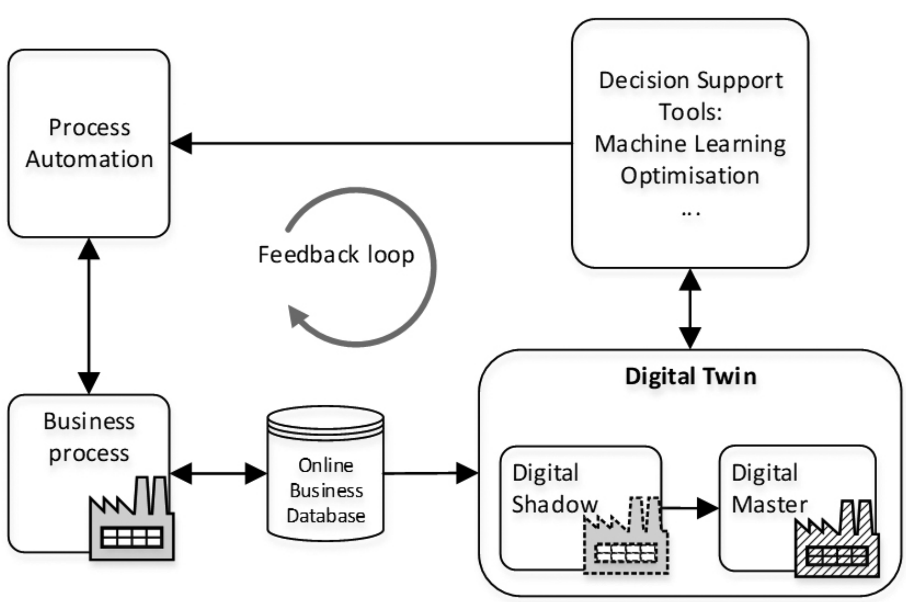

Figure 2: Schematic of a system implementing the new simulation modelling paradigm: a Cyber Physical Production System incorporating the Digital Twin

es of the single case, which can be viewed as unique and idiosyncratic (Yin, 2017). Further recommended reading on case study design includes (Yin, 2017) and (Merriam, 1998).

In this case, we present a holistic multiple-case study, aiming to explore and reason about the global phenomenon: *the new simulation modelling paradigm based on the Digital Twin concept*, and try to draw conclusions about the phenomenon, specifically about *the adoption of the new simulation modelling paradigm within projects for the industry*. In the following sections we present individual cases with focus on the simulation modelling aspect, the summary of the cases in the context of the new simulation paradigm, and the main lessons learned.

6 Cases of the adoption of the new simulation modelling paradigm

Implementing the new simulation modelling paradigm and the Industry 4.0 remains a serious challenge for researchers and companies. There are however novel ways to improve the integration of models built in general purpose simulation modelling tools, automate their construction and modification, and implement such solutions without major financial investments, which is a very attractive prospect especially for the SMEs. In this chapter we will examine multiple real-life cases of the implementation of the new simulation modelling paradigm, ranging from the development of a new methodology for high-level modelling automation to the development of a Digital Twin concept for SMEs.

6.2 Case: Methodology for High-level Modelling Automation

Thiers et al. (2016) describe the results project in a global aerospace company (Boeing), which aimed to improve the design of their production systems by addressing key questions earlier in the product lifecycle. These question have historically required the manual development of several statistical, discrete-event simulation, and optimization analysis models. Statistical, discrete-event simulation, and optimization analysis are capable of answering critically-important questions, but the time, cost, and expertise requirements for their usage in the status quo can be prohibitive for all but the largest companies. The developed solution automates several steps in the construction of these models, while allowing high customisation through the provision of requirements data by users. The company requirement was that the models are generated in commercial off-the-shelf (COTS) tools for automatically-formulated simulation models including Simio and Tecnomatix Plant Simulation. Authors have used the "personal assistant" (PA) user experience paradigm in the manner of Apple Siri/Microsoft Cortana/Google Voice Search in order to make their solution user-friendly and intuitive.

6.1.1 Problem description

The key challenge that authors (Thiers, Graunke, & Christian, 2016) describe was the automation of analysis formulation and solution. In parallel to PAs on mobile devices, answering questions about driving directions is possible because PAs already have detailed knowledge of civilian transportation networks. PAs no knowledge, however, of an arbitrary company's proprietary products, processes, resources, and facilities - and even if they did have access to the company's information systems, those are not complete, nor can commonly function in the required role of an experimental design environment.

There have been attempts automate engineering workflows, following the paradigm of separating system description from system analysis, authoring system descriptions in a presumably-easier way, and then automatically transforming them into the semantics and syntax of a particular analysis language as-needed. The authors however found none of the examined system description languages for productions systems is sufficient, and have decided to devise a way to accommodate a plethora of similar-but-different languages. Further obstacle was the lack of a canonical language for discrete-event simulation analysis. (Thiers, Graunke, & Christian, 2016)

6.1.2 Results

The methodology described by Thiers et al. (2016) places most of the transformation "intelligence" in the model-to-model transformations themselves, but introduces a small step forward by building simulation models to the greatest extent possible using model library blocks which are executable versions of bridging abstraction model elements. To enable the translation of requirements into model structure authors have introduced an intermediary step, called the "Bridging Abstraction Model". The novel modelling automation methodology schematic is shown in Figure 3. The Bridging Abstraction Metamodel is an abstract creation capturing the underlying commonalities shared by all discrete-event logistics systems – manufacturing systems, supply chains, warehousing & distribution systems, transportation & logistics systems, healthcare delivery systems, and more. The Bridging Abstraction Model is introduced to mediate a fundamental tension between concrete and abstract - a System Model should be as concrete as needed for accessibility, the Bridging Abstraction Model should be as abstract as possible for robustness and reusability, and efficacy depends on easily created and maintained mappings between the two. (Thiers, Graunke, & Christian, 2016).

The methodology's novelty is in its methods and tools which address large research challenges exist to make this work for systems engineering (Thiers, Graunke, & Christian, 2016):

- The Bridging Abstraction Metamodel: an explicit, analysis-neutral, and human- and machine readable metamodel which captures the underlying commonalities shared by all discrete-event logistics systems.
- Model-to-model transformations: to transform a System Model to a Bridging Abstraction Model in Figure 3, the mechanism has evolved from UML stereotype application, to declarative specifications in general-purpose transformation languages including QVT and ATL, to a custom model-to-model transformation language and engine.
- Understanding the space of questions about production systems and the analyses capable of answering them: This challenge is intimately related to deep domain knowledge. If and when an implementation of the methodology supports a critical mass of routine feasibility questions, a new challenge will arise - how to make productive use of a "question-answering genie" by asking the right questions. The authors envision that this will require capturing higher-level processes (diagnosis, continuous improvement, design, etc.) and the questions asked during each step of those processes' execution.

Authors (Thiers, Graunke, & Christian, 2016) also present a pilot case of modelling automation methodology use, wherein the developed the proof-of-concept software generates answers to the following engineering questions:

- What is the (expected) (Raw Cycle Time) of a certain (Job)?
- What is the (expected) (Throughput) of regularly executing a certain (Job)?
- What is the (expected) (Throughput) of making certain (Product)/s in a certain (Facility)?
- What is the minimum number of resources needed to support a certain throughput?

6.2 Case: Automated XML model building

This paper's relevance stems from the use of a novel automated DES model construction method, using the customer order data obtained with SQL queries to modify the XML (Extensible Mark-up Language) file containing the simulation model, thus altering the default model structure. The paper presents the methods and results obtained in a manufacturing process optimisation project. Authors used discrete event simulation (DES) to build a model that reflects the current manufacturing processes and allows them to test optimisation methods. Due to the large number of products and their manufacturing processes they have developed an automated model construction method that uses customer order data and manufacturing process database to build an ad-hoc simulation model. The model and method were tested in the optimisation task: reduction of product travel distance through modifications of factory layout, using a novel heuristic optimisation method based on force directed graph drawing. (Rodič & Kanduč, 2015)

6.2.1 Problem description

Construction of a DES simulation model requires that the data that describe the manufacturing processes are obtained, analysed, extracted and prepared in a suitable format for the model. In order to maintain model accuracy despite changes in manufacturing processes, integration of simulation software, auxiliary applications and databases

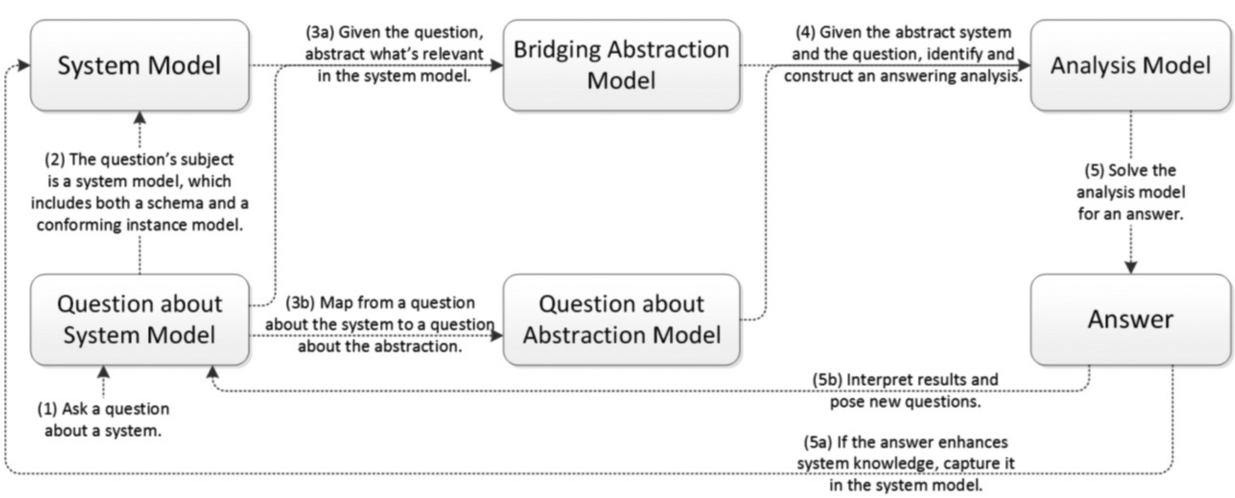

Figure 3: Novel modelling automation methodology described by Thiers et. al (2016)

is necessary. Optimisation through modification of model structure can be performed by constructing several versions of the model and input data (i.e. scenarios) and comparing simulation results. To accelerate the development of model versions and scenarios one can construct algorithms that build or modify simulation models according to model input data. This is especially useful in cases of large simulation models and if the model variants are prepared by an algorithm, e.g. an optimisation algorithm. Automated model building and modification however requires that the model structure can be modified with an algorithm, without manual interventions. (Rodič & Kanduč, 2015)

Developing a static simulation model that would cover all possible (i.e. 30,000) products that may appear in client's orders is not realistic as it takes approximately 15 minutes to complete a model of a process for each product, and a model containing 30.000 process also exceeds the memory limitations of the modelling tool used (Anylogic, http://www.anylogic.com/). Manual modifications of the simulation model can be time consuming, especially if a large set of variations of the model needs to be built. In Anylogic, simulation model is typically constructed by adding different blocks and connections to the canvas by "click and drag" technique. Instead, a method for ad-hoc model construction for each set of open orders was developed. The method works by modifying the XML file containing the Anylogic model. (Rodič & Kanduč, 2015)

6.2.2 Results

As orders change continuously, authors have developed a method and application in Java that automatically builds the model from a model template, the database of technical procedures and the database of currently open orders. Based on the list of ordered products and technical procedures only the necessary machines are placed in the model. Anylogic stores the models as standard XML files, which allows easy manual or algorithmic modifications of the model. Anylogic XML simulation model file stores information on standard and user-defined blocks and agents, connectors between blocks, statistical monitors, input readers, output writers, etc. The data are stored as elements (nodes) and nested in a tree-like structure. An element can contain several attributes, describing type of the element and all the parameters describing element properties. The attributes can contain several lines of programming code describing how the block operates in different situations and states. (Rodič & Kanduč, 2015)

The developed Java application manipulates XML code to change data on machines and all other relevant abstract objects such as connectors, sources and sinks that are connected to the blocks of machines. Specifically, the Java application reads the blocks in the template file and copies them according to input data. A new element (block) is added to the model by the following procedure:

- find a node representing a template block in XML tree according to the searched attributes,
- copy the node and connect it to the parent of the original node,
- change the data of the copied block (name of the block, position on the canvas, properties of the block, part of the programming code, etc.).

The resulting XML structure is then saved to a new Anylogic file. Products and carts play a role of transactions in DES and are therefore constructed dynamically during simulation. The resulting modelling and simulation system, shown in Figure 4 is composed of four main elements

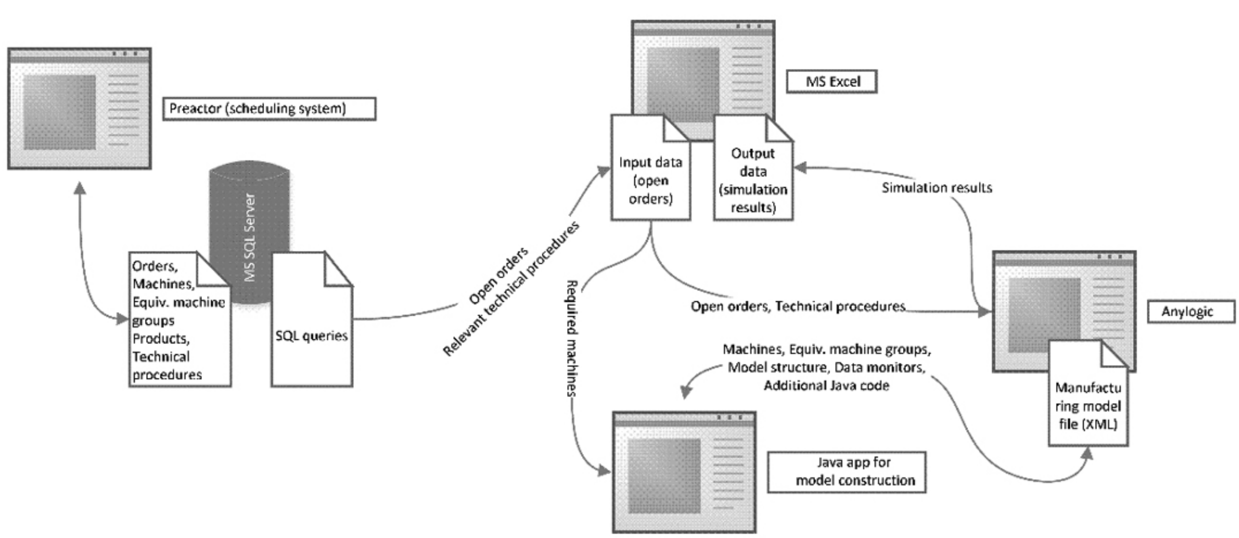

Figure 4: Schematics of a system implementing automated DES modelling (Rodič & Kanduč, 2015)

(Rodič & Kanduč, 2015):

- Core manufacturing process simulation model in Anylogic environment. Layout of the machines and paths was generated from the AutoCAD model of the factory.
- Java application that constructs XML Anylogic model from a template file.
- MS Excel as an intermediate input and output data storage, and analysis tool. MS SQL server database describing technical procedures and client's orders.

6.3 Case: ERP Data-driven Automated Modelling

Kirchhof (2016) describes a practical case in which entire simulation models of a complex and large scale automotive flow shop production are automatically created from an automotive company's SAP ERP and MES systems in order to support operational planning purposes and reduce operational logistical risks.

6.3.1 Problem description

Automatic model generation, the consequential reduction of problem solving cycles and the need for a higher degree of data integration have long been characterized as significant challenges in the field of simulation of manufacturing systems. Especially operationally used manufacturing simulation models re-quire a high degree of modelling detail and thus depend on a significant amount of input data. In many cases, the time and effort required to manually build such a detailed model and keeping it up-to-date are prohibitive. Automatic and on-demand generation of entire simulation models from company data sources would significantly increase the applicability of simulation for operational planning purposes. (Kirchhof, 2016)

6.3.2 Results

In the automotive industry lean production principles are widely implemented, obliging companies to balance cost saving inventory reduction activities and operational risks, such as stock-out situations at the manufacturing line. The purpose of the described simulation model is to act as an early-warning-system and detect potential stock-out situations before they occur so that counter-measures can be assessed and initiated. Therefore, the scope of the model covers the entire in-house logistics processes of the company from the parts retrieval in the warehouse to the consumption at the manufacturing line. (Kirchhof, 2016)

A generic flow shop simulation model template capturing the company's specifics was developed using the SIMIO simulation modelling tool. To enable modelling automation, a custom built extension to SIMIO was developed, that allows modification of a blank model by placing specific instances of the modelling elements according to input data. Extension can generate entire flow shop models by automatically placing, connecting and parameterizing the predefined model objects within the model. The data required to generate the model is extracted from the company's SAP and MES system using a custom built data extractor software which directly retrieves the relevant data from the respective system's databases. The SAP system provides the information to model the manufacturing line, such as details about workstations, routings, bills of materials, shift plans, manufacturing orders, stock levels, material master data etc. The MES system provides detailed information about production sequences and the current and planned production progress per workstation and manufacturing order. The resulting simulation solution is fully integrated into the operational planning process and the IT architecture of the company, and helps planning personnel of the company to prevent logistical problems and production disruptions. Due to the automation of modelling the problem solving cycle is significantly reduced compared to the manual method. The presented approach is suitable for large-scale models with a high degree of modelling detail. (Kirchhof, 2016)

6.4 Case: Standards based virtual factory modelling

Jain and Lechevalier (2016) describe the method and proof of concept for automatic generation of virtual factory models using manufacturing configuration data based on data standard formats such as XML. The virtual factory in this context represents a high fidelity, multi-level simulation. Modelling and simulation has been identified as the key to the advancement of manufacturing by a number initiatives, such as smart manufacturing and Industry 4.0 have identified. Proposals include the use of simulation at multiple levels within manufacturing, with heterogeneous models ranging from physics-based models of the manufacturing process at a very detailed level to DES and SD based high level supply chain models. The method proposed by authors (Jain & Lechevalier, 2016) is aimed at automated construction of a comprehensive, high detail virtual factory model, i.e. a Digital Twin.

6.4.1 Problem description

Currently the development of a Digital Twin requires considerable resources and expertise, limiting the accessibility to bigger companies to the disadvantage of SMEs. Automatic, data-based model generation has the potential to reduce the expertise requirement and thus facilitate the increased use of simulation. The proposed method augments the existing automation solutions by proposing the use of standard data formats for input data describing the subject manufacturing system and widening the generated model scope to a virtual factory model as defined with multi-resolution capabilities rather than the single level model. (Jain & Lechevalier, 2016)

6.4.2 Results

The proof of concept implementation of the method uses Anylogic as the simulation modelling tool, with multi-level modelling implemented by using Java code for the process model, agent based modelling (ABM) to model the machine level, and DES models for the cell/process chain level, similar concept as described in (Rodič & Kanduč, 2015). Integration of different modelling methods is achieved through native capabilities of the Anylogic tool, resulting in a hybrid model. Hybrid modelling has been historically achieved by connecting the models via middleware solutions (Rodič & Kljajić, 2005). The schematic of the proposed method is shown in Figure 5.

The operation of the proposed automatic generation approach is described below (Jain & Lechevalier, 2016):

1. read the manufacturing system configuration data via an interface supporting in a standard format,
2. read in machine parameter and process level data,
3. assemble the factory or cell level logic network based on the input process plans data,
4. link the factory or cell level logic network to individual machine and corresponding process,
5. generate the model using the corresponding models available in the library,
6. render the layout of the facility based on the information from the configuration data with links to the logic network,
7. execute the model with selected parameters such as resolution level and output formats selected by users via run-time interaction.

The data-based modelling interface uses data in CMSD format, which is based on XML. A Java parser has been developed to go through a CMSD file for the machine shop and collect the information required to automatically build the corresponding virtual factory model. The author's (Jain & Lechevalier, 2016) objective is to automatically generate a virtual factory model, using data from the real factory in applicable standard formats, with the capability of generating output data streams based on other applicable standards formats. The automatic generation of the virtual factory model is intended to go beyond the previous efforts involving automatic generation of single level factory simulations by generating a multi-resolution model and using standard formats of input files.

6.5 Case: A Digital Twin for SMEs

Uhlemann et al. (2017) present a concept for the realization of a Digital Twin of the production system within SMEs. Their concept is feasible by assuring sufficient data quality with minimized investment costs, and without compromising the advantages of the Digital Twin and of the CPPS. Their concept contains the proposal for database structure and guidelines for the implementation of the Digital Twin in production systems in SMEs. The further concept of the Digital Twin for a production process enables a coupling of the production system with its digital equivalent as a base for an optimization with a minimized delay between the time of data acquisition and the creation of the Digital Twin. This allows the construction of a cyber-physical production system, opening up powerful applications. To ensure a maximum concordance of the cyber-physical process with its real-life model, a multimodal data acquisition and evaluation has to be conducted.

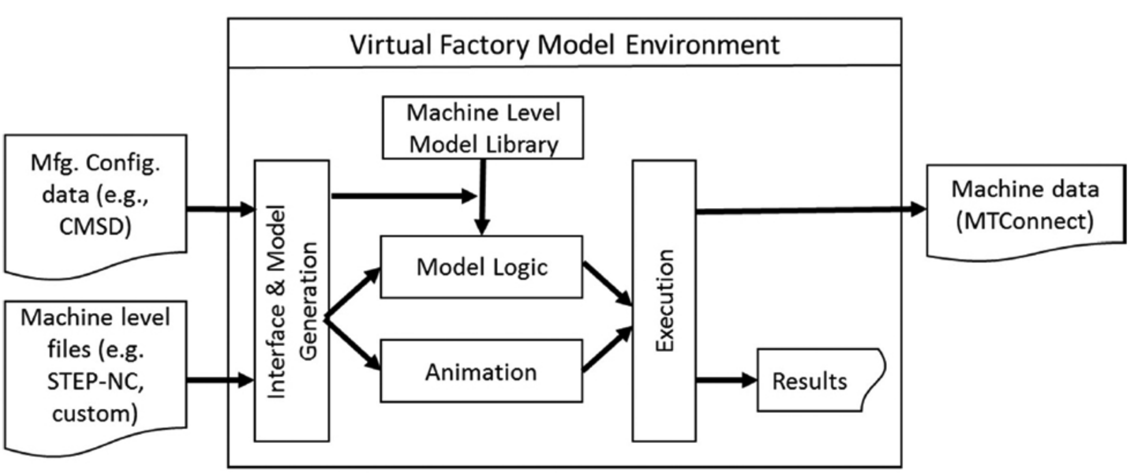

Figure 5: Standard data format based modelling automation system schematic (Jain & Lechevalier, 2016)

6.5.1 Problem description

In recent years, Industry 4.0 is one of the most prevalent subjects in production engineering. However, methods of Industry 4.0 are currently still under-represented within manufacturing operations. Authors furthermore describe the following difficulties in the course of the realization of the Digital Twin as an essential precondition of a CPPS (Uhlemann, Lehmann, & Steinhilper, 2017):

- manual acquisition of motion data is widely used, though in conflict with necessary real-time availability,
- manual acquisition of motion data snapshots limits the potential of simulation,
- combined with decentralized data acquisition, a central information system is required ,
- in-house implementation of Industry 4.0 concepts is frequently insufficient,
- slow standardization of data acquisition in productions systems hinders agile and adaptable system implementations,
- standardization of data acquisitions has not yet been achieved,
- high costs for new IT-environments inhibit the application of vertical Industry 4.0,
- coupling of simulation and optimization is not sufficiently ensured to take full advantage of near real-time models, and
- data security concerns.

The acquisition of motion data combined with data on employee activity as well as position and use of production machines forms a great potential for the realization of a CPPS. Especially in SMEs, which generally have a low degree of automation, existing time-dependent position data sources and databases are not sufficient. A comprehensive image of the production system can only be achieved if additional information of movements of employees and means of production are considered. A comprehensive image of the reality within a production system therefore can only be achieved through a multi-modal data acquisition, similarly to the procedures in modern self-driving automobiles. (Uhlemann, Lehmann, & Steinhilper, 2017)

6.5.2 Results

As the database of production data in SME is extremely heterogeneous and its quality regularly insufficient for the realization of the Digital Twin, the authors (Uhlemann, Lehmann, & Steinhilper, 2017) introduce sensor based tracking and machine vision for manufacturing process data acquisition. Sensor-based tracking provides information regarding routes and position of production employees and routes and position of large and highly mobile production devices, e.g. forklifts. The required technologies, i.e. sensor-based tracking systems and extensive program libraries for the machine vision implementation are commercially available, and therefore the implementation of the proposed concept is feasible. Sensor-based tracking is to provide information regarding routes and position of production employees and routes and position of large and highly mobile production devices, e.g. forklifts, while the image recognition enables detection and identification of types of products at the production and smaller machines.

Authors (Uhlemann, Lehmann, & Steinhilper, 2017) propose the next step as the development of a virtual production system, which generates data following the real production system with the two implemented data acquisition technologies. Based upon this, the data layer and the information and optimization section are constructed and verified trough testing. In the last step, the data acquisition hardware is implemented into a real model process and linked with the data layer. This forms the final and major step within the realization of the CPPS in SME as part of the presented concept. The schematic of the proposed Digital Twin concept is shown in Figure 6.

The described concept is novel in comparison to approaches prevalent in large enterprises, which focus on full automation. Automated gathering of machine data is not considered, as the low degree of digitalisation of manufacturing in SMEs data does not allow it. Furthermore, the collection of detailed machine data is not required with the presented concept. The innovative aspect of the concept is in the integration of well adopted and commercially available components, which are already available as isolated solutions. (Uhlemann, Lehmann, & Steinhilper, 2017)

7 Conclusion

7.1 Lessons learned

In this chapter we summarize the main conclusions and lessons learned from the presented multiple-case study. From the examined cases we can conclude, that while the new simulation modelling paradigm and the Digital Twin concept are being adopted by large and small companies, there are significant differences in problems that they face, and the methodologies and technologies they use to overcome the issues. The large players in airspace (Thiers, Graunke, & Christian, 2016) and automotive industries (Kirchhof, 2016) are concerned with the development of standardized methodologies and architectures that would allow integration within their R&D processes and existing ERP and MES solutions, and the purchase or development of automation technologies is not presented as problem, probably due to large available resources, the SMEs are more focused on using economical, off-the-shelf simulation modelling tools (e.g. Anylogic) and commercially available sensors to build proprietary automation

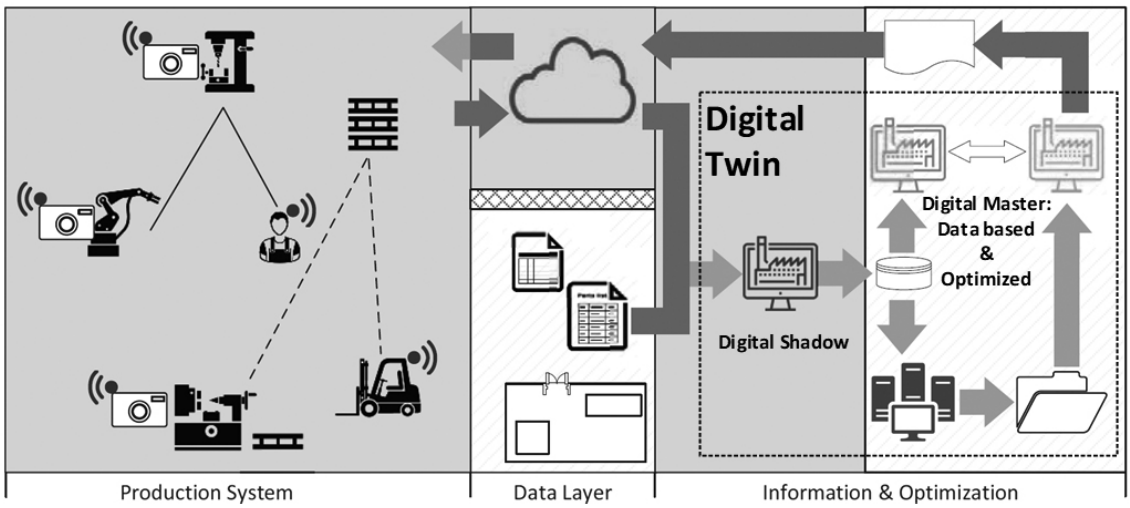

Figure 6: Concept of the CPPS through the Digital Twin in SMEs - adapted from (Uhlemann, Lehmann, & Steinhilper, 2017)

solutions, which would allow them to implement selected Industry 4.0 concepts, in order to remain a competitive supplier to their (larger) business partners.

Even when companies are not consciously implementing the Industry 4.0 paradigm, the pressure from their competitors or partners will require them to do so. The motivation for using the new simulation modelling paradigm concepts such as online automated modelling and database integration can originate from the demands of modelling a modern, diversified manufacturing process. In (Rodič & Kanduč, 2015), data based automated model building was the only option to construct the model of the manufacturing process for any given set of orders in an acceptable amount of time. On the other hand, even the largest companies like Boeing are stimulated by the promise of large-scale cost reduction and design process acceleration to invest in development of new methodologies allowing automation of simulation modelling and customization of products early in the product lifecycle (Thiers, Graunke, & Christian, 2016). Automotive industry is known as an early adopter of Industry 4.0 concepts, however many aspects like ERP and MES integration still lack standardization (Kirchhof, 2016).

7.2 Discussion

Currently, methods of Industry 4.0 are under-represented within manufacturing operations. This is, on one side, based on non-uniform definitions of Industry 4.0, an issue that current publications counteract against. On the other side, common difficulties as non-existing standards, uncertainties regarding the economic benefits while facing the requirement of sometimes considerable investments. Within a 2015 German Mechanical Engineering Industry Association (VDMA) survey, only 10% of those surveyed stated to have implemented comprehensive acquisition of process and machine data. Only a third applied the gained data in a feedback based production control system. Especially the low degree of automation in SMEs reveals a great requirement for alternative approaches for the realization of CPPS. (Uhlemann, Lehmann, & Steinhilper, 2017)

The research presented in this paper includes novel solutions, that allow researchers and engineers to develop solutions that automate the model generation and solution seeking aspects of simulation based decision support and engineering systems. Presented methodologies and solution allow the automation of general purpose / off-the-shelf simulation modelling tools by using ERP/MES data and standards, and the development of Industry 4.0 automation solutions using the Digital Twin concept with widely available sensor technologies. Design-to-production transition is a complex business process, and the described research results supports that process by enabling designers to appreciate production consequences of design decisions much earlier in a program's design cycle than is possible today (Thiers, Graunke, & Christian, 2016).

An unanswered challenge for the multi-level modelling is model validation, which can prove to be a challenge for automatically built models, especially for multi-level models. Each simulation model has to be validated carefully including the impact of intrinsic and extrinsic uncertainties. All the physics-based process models have to be validated against real machine processes and their ranges of applicability defined. A one level of such a model depends on the outputs of another, the multi-level model results in stacking of validity uncertainties across the multiple levels. The impact of stacking of uncertainties needs to be understood and quantified before the virtual factory and other multi-resolution models can be used to support decision making in industry. (Jain & Lechevalier, 2016)

The adoption of new simulation modelling paradigm in research environment requires closer cooperation with industry partners, and diversification of knowledge of researchers, in order to build integrated, multi-level models of systems. As shown by the presented cases, lack of tools is not a problem, as the current generation of general purpose simulation modelling tools offer sufficient integration options. Furthermore, a number of solutions have been developed for automatic generation of simulation models corresponding to manufacturing systems, with a good overview of solutions presented in Barlas and Heavey (2016). As the multi-level modelling requires the integration of model built using different methodologies and tools, the Industry 4.0 and Digital Twin concept present researchers with a new motivation for closer cooperation and transfer of knowledge between research groups and institutes.

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