Contrasting Digital Twin Vision of Manufacturing with the Industrial Reality

Savolainen Jyrki, Knudsen Mikkel Stein

DOI: 10.1080/0951192X.2021.1972471

Contrasting Digital Twin Vision of Manufacturing with the Industrial Reality

Jyrki Savolainen[1], Mikkel Stein Knudsen[2,3]

[1] *LUT School of Business and Management, LUT University, Lappeenranta, Finland;*
[2]*Finland Futures Research Centre, University of Turku, Turku, Finland;*
[3]*Faculty of Social Sciences, Business, and Economics, Åbo Akademi University, Turku, Finland;*

Corresponding author:
Dr. Jyrki Savolainen,
Yliopistonkatu 34, 53850 Lappeenranta
jyrki.savolainen@lut.fi
ORCID: 0000-0001-9721-642X
https://fi.linkedin.com/in/jyrki-savolainen-a617333

Contrasting Digital Twin Vision of Manufacturing with the Industrial Reality

This paper discusses the value proposition of a system-level Digital Twin (DT) in the context of complex manufacturing processes from the managerial perspective. The central promise of DT-technology is to use and iterate the available real-time process information in a simulation setting transforming it instantly to operational or managerial-level decision-making implications. Despite the clear potential of this emerging technology, a gap of knowledge exists on how such DT could be implemented and what would be its defining features. The key contribution of this research is to lay out the central discrepancies between the promise of digital twin technology vision versus what is possible within the limits of current industrial infrastructure in the short- and mid-term. This research builds on the currently existing scientific literature which we use to point out ten foundational issues of system-level digital twins that are analyzed and discussed in detail. As a conclusion, we propose that large system-level DT-projects have a managerial rationale only when several preliminary conditions are met and fulfilled.

Keywords: digital twin; simulation; investments; cyber-physical system

1 INTRODUCTION

Digital Twin (DT) is an emerging concept, which by broad definition refers to (a set of) digital models of physical entities usable for optimization and decision-making purposes based on real-time digital information (see, e.g., Negri, Fumagalli, and Macchi 2017; Tao et al. 2018; Redelinghuys, Basson, and Kruger 2019). This research discusses the preliminaries and pre-requisites of "digital twinning" of the large and complex industrial systems within the context of automated and data-driven manufacturing or "Industry 4.0" (see definition in, e.g., Kemper et al. 2014).

Originally the idea was coined in the aeronautics industry, (see, e.g., Rosen et al., (2015); Tuegel et al., (2011)), to predict NASA's aircrafts' structural lifetime over a range of missions. Indeed, Madni et al., (2019); Stark et al., (2017) and West and Blackburn, (2017) write that the distinct feature of digital twins versus digital models is that a DT represents a specific asset or instance with unique peculiarities and history. The possible uses of digital twins on a high level are described in many studies, e.g., in Cimino et al., (2019); Madni et al., (2019); Negri et al., (2017) and Tao et al., (2018).

Digital twins for manufacturing have also captured the attention of scholars and practitioners. However, when it comes to building DTs of whole manufacturing systems (MFS), the concept is yet unclear and the existing literature is at an exploratory stage (Min et al., 2019; Negri et al., 2017; Q Qi and Tao, 2018). MFS is used here in a broad sense to refer to industrial-scale processes that transform raw material(s) into a product(s) concentrating on the aspects of manufacturing, where DTs are used for optimization purposes in connection with simulation, "the third mode of science" (see discussion, e.g., in Hu et al., (2006); Mei and Thole, (2008)). Although previous research has trailblazed several directions of theoretical research on this topic, practical case examples are rare (Kritzinger et al., 2018). Lu et al. (2020) claim that the lack of understanding of the digital twin concept has inhibited industrial adoption. This paper addresses the structure and practical implementation of the digital twin of manufacturing systems from the organizational and managerial point of view. It furthermore questions whether a system-level digital twin – or more precisely a digital twin of manufacturing *systems* (MFS) – is something that, within the current limits of technology, has an adequate payback or option value that makes it worth investing the time and money required. This research derives ten generalized propositions for evaluating the applicability of digital twins concerning manufacturing system applications. These propositions fill a major research gap, since there is a distinct lack of high-level digital twin frameworks in the digital twin/manufacturing system literature.

The ten propositions originate from several questions related to system-level digital twins that include: identifying a suitable general level structure/software platform, the required data and minimum/maximum data granularity on which the system-level DT could in principle operate, and where the most likely economic value-added would be for DT-investments at this point.

The article suggests that managerial considerations on digital twins must distinguish between digital twins for specific manufacturing equipment and digital twins for MFS. When multiple real-time operating digital twins form a system, "digital twin aggregate" (DTA), the blink-of-an-eye operation assumption breaks down due to added detail, computational complexity, and, sometimes even, the laws of physics in electronic communication (see discussion, e.g., in Redelinghuys et al., (2019) and Zheng and Sivabalan, (2020)). DTAs are different and a much more challenging proposition than Digital Twin Instances (DTIs) (cf. Grieves, (2019)). Therefore, it is suggested here that striving to implement 'visionary' system-level digital twins for managerial purposes might not be, in the short to medium term, optimal use of resources. To avoid a trough of disillusionment due to unfounded expectations, suggestions are made for immediate avenues of applying MFS DT within the current limits of technology and managerial practice.

The paper continues with a detailed definition of a digital twin, which is followed by a semi-structured literature study of the already existing contributions. This highlights the lack of similar previous publications akin to this one. In chapter four, the founding characteristics of a digital twin of manufacturing are summarized in ten propositions, which are then applied to envision some focused directions of development. The authors believe these propositions will help to navigate a way forward for the successful adoption of digital twins in manufacturing industries. Chapter five illustrates a generic framework application in which we illustrate how our propositions could be utilized in practice. The paper closes with conclusions and propositions for future research.

2 THEORETICAL FRAMEWORK

Digital twins are highly detailed computer models that interact with physical reality (Alam and Saddik, 2017). Kritzinger et al. (2018) state that only virtual models that transmit data in and out of the virtual space can be regarded as digital twins. In other words, the co-existence of physical and virtual worlds is of the essence in any cyber-physical system (CPS) or CPPS (cyber-physical production system) in which a digital twin, according to Kunath and Winkler (2018), can be understood as the digital part. Integral to digital twin models is the ability to communicate calculated, data-based insights to its user, which means some type of human-readable, semantic, data-model of reality (Kunath and Winkler, 2018; Negri et al., 2017). Shao and Helu (2020) claim that real-time visualizations are the key innovation of digital twins. For a more comprehensive review of digital twin definitions, see, e.g., Negri, Fumagalli, and Macchi (2017); Kritzinger et al. (2018); Jones et al. (2020); Ciano et al. (2020).

The origins of digital twin -ideology may be traced back to two separate origins: design and simulation perspectives (see **Table 1**). The design perspective (M. Grieves, 2017; Madni et al., 2019) emerges from the increasing capabilities of *Computer-Aided Design* (CAD) to model and visualize physical objects with an unprecedented level of physical details. Parallel to this, there is a more abstract idea of the “next level of simulation” using integrated, co-operating sub-models (Bao et al., (2019); Kunath and Winkler, (2018)), or *model-based systems engineering,* MBSE (Rosen et al., 2015). This article is in the vein of the simulation perspective, seeing digital twins of manufacturing as advanced simulation models with some degree of aggregation. This follows the previous works of, e.g., Rosen et al. (2015) who define digital twin-based simulation as a primus motor for constructing autonomous (industrial) systems.

Table 1. A summary of two paradigms of the digital twin concept. *Legend:* DT = Digital Twin (summarized from Bao et al., (2019); Grieves, (2017); Kunath and Winkler, (2018); Madni et al., (2019); Rosen et al., (2015); H. Zhang et al., (2017)

Digital Twin	**Design paradigm**	**Simulation paradigm**
Aim (primary)	Design and Operation	Operation and Optimization
Representation (primary)	High detail and visual	Low detail and illustrative
System type	Simple / Complicated	Complicated / Complex
Physics model (ideal)	Atom level	Aggregate phenomena
Unit of modeling	Piece of equipment	Connected processes or events
Virtual Environment (VE)	DT as part of VE	DT itself as VE
Data included (ideal)	All possible	All relevant
Level of aggregation	Low as possible	Dynamic / based on application

The design-simulation classification is by no means exclusive; other studies, such as Kunath and Winkler (2018), suggest combining several Digital Twin entities that are then simulated in parallel. Zhang et al. (2017) propose that in the design of production plants, the CAD-perspective may be related to building an immersive (static and visible) virtual experience of the factory, whereas in the system simulation one is interested in improving (dynamic and indirectly visible) performance, efficiency and quality of it during the actual production.

Prior studies have also already identified several challenges for the technological implementation. Zhang et al. (2017) point out the very lack of conceptual basis of DTs. Müller et al. (2018) raise the issue of feasibility, in terms of data collection, storage, and representation. Kunath and Winkler (2018) are concerned about the low availability of relevant data. Also, there are evident challenges in synchronizing data between virtual and physical space (Tao et al., (2018)); merging data from different information systems (H. Zhang et al., 2017); transferring data between digital twin instances (Yuqian Lu et al., 2020); or from the virtual world to physical (Cimino et al., 2019). Grieves and Vickers (2017) highlight the organizational barriers around building digital twins as there are no naturally occurring information flows between functional boundaries, and multi-domain models are rare. Cimino et al. (2019) note that most of the reported DT-implementations are not scalable to the production line level. To realize the promises of fast decision support based on DTs behavior, according to Liu et al. (2019), a lot of work remains to be done around the mathematical approximation methods of modeling results. It is clear that there is a range of generic technical challenges, which a successful implementation of DTs must take into account, especially in system-level settings.

The behavior of any system originates from its type. According to Grieves and Vickers (2017), there are three types of systems: simple, complicated, and complex. Simple systems are, indeed, simple and predictable. Modern manufacturing processes are often complicated, but predictable: the connection between components is known, and if the inputs are known, the resulting outputs are also known. In complex systems, however (ibid.), combined actions of different components can lead to unexpected consequences that are not visible or immediately comprehensible. **Figure 1** illustrates the paradigm shift from building an independent digital twin (e.g. aircraft) to creating a digital twin aggregate with simple interactions (e.g. airplane traffic) and finally arriving into a system-view of DTs with complex interactions applicable for manufacturing processes.

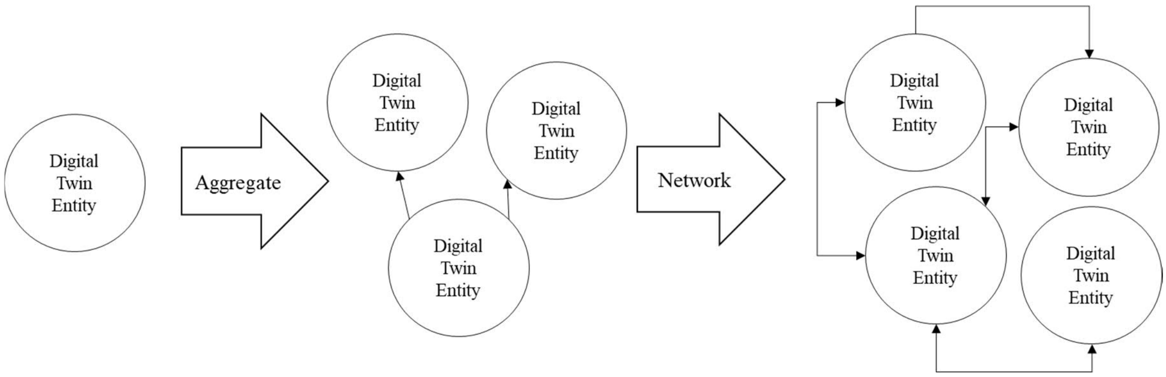

Figure 1. Digital twin technology: from single DT to system-level DT.

In the context of system behavior, Gabor et al. (2016) discuss the ability of digital models to produce *planned reactions* based on simulations instead of resorting to fixed behavioral rulesets that are pre-programmed. Rosen et al. (2015) use a distinction between automatic and autonomous operation, where the former refers to ready-made sequences and the latter to performing tasks or sequences based on the represented knowledge.

The focus of this article is the digital twin's envisioned ability to understand and autonomously harness the system-level complexity of MFS, which, combined with managerial technology adoption, could be turned into economic value. In practice, connecting the available data and by probabilistic prediction of the future values, the simulation-based digital twin could "front-run" production system in real-time based on the constantly updating data and thus present a window in the future in terms of possible system states to facilitate/automate decision making (for further discussion, see, Kunath and Winkler (2018); Grieves and Vickers (2017); Rosen et al. (2015); Gabor et al. (2016)). The idea is in no way new: already, in the early years of computers, Kleijnen (1979) wrote methodological ideas to generalize simulation results instead of reporting ad-hoc insights, but he was not likely even imagining the real-time aspect. Grieves and Vickers (2017) highlight that the front-running capability is required to run faster than the physical activity itself or at least, according to Kunath and Winkler (2018) the decision-making should be fast enough not to cause disruptions in the physical system. This requires faster than real-time simulations (Zhidchenko et al., 2018).

Following the ideas of Jung et al. (2018), the digital twin can be more than an ultra-realistic simulation of a system: when supplemented with intelligence – referring to automated statistical analyses of data – it can be used for real-time decision making support and optimization. While simulating complete manufacturing plants with several production systems and stochasticity is a complex and computationally heavy task, it contains enormous potential for efficiency increase that is worth the investment (see, e.g., Lidberg, Pehrsson, and Frantzén 2018).

3 LITERATURE STUDY

This literature study is divided into two parts. In the first part, the managerial aspects of simulation-based digital twin are addressed using a systematic keyword search relevant to this article. The second part of the review deals with the more detailed technical aspects.

Numerous reviews on the topic of digital twin from technical perspectives are already available and therefore no attempt to repeat previous research efforts is taken here. For the reader interested in extensive reviews, see e.g. the following: Negri et al. (2017) present a timeline of how the definition of a digital twin has evolved. Kritzinger et al. (2018) observe that the majority of current research deals with the conceptual level of digital twins in the context of production planning and control and that the number of case studies is sparse (see also Yuqian Lu et al. 2020). The review by Cimino et al. (2019) lists the two most important roles of digital twins as either supporting production system management or monitoring and improving the production process. Errandonea et al. (2020) extensively review the application of digital twins for predictive maintenance. Ciano et al. (2020) provide a bibliometric review of digital twin-enabled smart industrial systems, while, finally, Liu et al. (2020) present a comprehensive and up-to-date review of the field and current industrial applications.

Even though some authors (e.g. Wright and Davidson (2020)) consider the term Digital Twin overused already, it is surprising how sparse the academic literature on managerial, organizational, and business implications of digital twins of manufacturing systems remains. Scoping the existing literature for this article, a systematic search was carried out in the academic SCOPUS-database in October 2020 (updated on May 2021) for titles, keywords and abstracts on managerial, organizational, and business implications of digital twins for manufacturing:

> TITLE-ABS-KEY (*digital twin** AND (*managerial* OR *organisational* OR organizational OR *business*) AND *manufact**)

While the number of identified articles has grown rapidly during the writing of this article, the search result (from Oct 2020 to May 2021) remains a relatively sparse 115 entries of which, the most relevant results are believed to be covered below. For most of the identifiable publications, these managerial-focused implications serve only as an addendum to a primarily technical focus. Unsurprisingly, the literature on these implications of digital twins of manufacturing *systems* is even more limited. Out of the 115 articles, less than 30 articles even tangentially cover this topic. None of the previous publications provide generalized propositions or a generic framework similar to this article.

Managerial-focused literature

Waschull et al. (2018) analyze the close links between product digital twins and Manufacturing Execution Systems (MES) based on an aerospace industry case study. The article finds that MES takes on an increasingly central role in the automation pyramid (from process automation to decision making) with digital twins central to the sphere of MES. Qi et al. (2018) discuss the servitization of digital twins. It is central to their argument that digital twins for manufacturing systems do not need unique models created by each manufacturer, but that optimized business behavior often suggests buying external models and fitting them to the manufacturers' local contexts.

Lu and Chu (2018) stress that to succeed in operational contexts, more 'human-friendly' digital twin tools are needed, e.g. with standardized digital twin templates and eventually drag-and-drop applications of cyber-physical systems. Cheng et al. (2018) seek to overcome the existing challenges of digital factories through four dimension-framework, albeit without much discussion of the practical, economic feasibility of the proposed. Wagner et al. (2019) argue that there remain key future research challenges for linking digital twins in the industrial environment. For broad industrial applications to happen, consistent practice for the holistic use of digital twins in the entire product development must still be defined, including research progress in topics of mutual understanding, interfaces, standardization, and efficient information flow.

Stark et al. (2019) introduce a "Digital Twin 8-dimension model" where each dimension provides three or four levels of realization, and a higher level is not necessarily better; it just depicts a different realization space. The model thus underlines that 'digital twin' is not a one-size-fits-all concept, and that, as an important managerial implication, investments in various functionalities of digital twins should reflect situational needs. Guo et al. (2019) proposes modular digital twin approaches for flexible factory design for two main reasons. First, a modular approach allows faster construction of selected parts and thereby quicker access to potential benefits of the digital twin investment. Secondly, the uncertainty involved in each design step is easier to navigate with a modular approach.

Murphy et al. (2020) devise ways of integrating financial data streams into the digital twin simulations. This is a highly relevant contribution to digital twins as a business optimization tool. Li et al. (2020) and Bevilacqua et al. (2020) have proposed novel digital twin-models and discuss their managerial implications for enhancing respectively process operators' safety and sustainability. Wang et al. (2021) discuss digital twins as an enabler of shared manufacturing. An analysis by West et al. (2021) highlights three main implications in the managerial context. First, DTs support joint decision-making by translating technical considerations into business contexts. Second, DTs visualze the multiple perspectives of actors, roles, and motivations to reduce complexity in decision-making. As the last point, West et al. (2021) point out that, at this stage of technology, value-added exploitation inside a firm may be simpler to achieve than utilization for external commercialization of new value propositions.

Technology-focused literature

Madni et al. (2019) use a four-level classification of DTs where the lowest, level 1, corresponds to the digital prototypes and the highest, level 4, "Intelligent" Digital Twin uses machine learning-based data analyses to draw insights about the current state and future course of the system based in uncertain and only partially observable environments. Cimino et al. (2019) discuss the positioning of DT versus the five-level "pyramid of automation" in manufacturing, where the lowest level (nr. 0) is the process automation (e.g. Distributed Control System, DCS) and the highest (nr. 4) deal with the planning of days/weeks or months ahead (ERP). They seem to interpret this hierarchical automation construction as more of a barrier for DT applications than an enabler. Stark et al. (2017) observe that current mechanic-centered practice in building manufacturing systems out of its smallest parts does not support holistic, more software-centered, designs based on functional units with versatile executable functions. They propose an approach, where independent CPSs would execute flexible process chains based on mutual negotiations on the Pareto-optimal way of execution.

Redelinghuys et al. (2019) develop a six-layer technical architecture for digital twin technology which supports a wide variety of software and tools in different layers. A laboratory-level digital shadow is described in Cimino et al. (2019). Ayani et al. (2018) discuss the digital twin concept in the context of machine recommissioning projects, where existing process data can be used to imitate past behavior. Using the contemporary terminology Qi and Tao (2018) provide a discussion on the relationship between the digital twin and big data. Liu et al. (2019) apply digital twins to optimize the Automated Flow-Shop Manufacturing System (AFSM). They use a bi-level programming approach in which first a static optimization is performed with regards to, e.g., the number and capacity of different equipment, and then a dynamic simulation is performed to identify possible issues. Min et al. (2019) report difficulties in dealing with the dynamic process in their research of a digital twin model for petrochemical industry operation where they strive for simultaneous optimization of process parameters in five major facilities and a total of over four hundred control indicators using plant's available data sources. Although performance improvement is reported, they highlight that the DT build aims to optimize the current process parameters, but not the overall optimal in terms of economic benefit.

Kunath and Winkler (2018) present a conceptual DT-model to support the control of the order management process. Min et al. (2019) suggest the following generalized process to implement a digital twin for the petrochemical industry: building a digital framework; applying ML-methods to train and optimize the model with historical data;

deploying the model by connecting it to real-time data. Zhang et al. (2019a) propose a reconfigurable modeling approach that can satisfy varying granularity needs of data across the manufacturing system.

Liu et al. (2019) write that the current DT-works concentrate on the synchronization between real and virtual worlds lacking the considerations on how to perform online optimization of complex systems with coupling relationships (e.g. a solution of one problem may produce parameters of another problem), where isolated optimization efforts are out of the question. Indeed, there are still only very few mathematical methods that can deal with multiple interconnected units in a time-continuous and probabilistic environment (see, e.g., Min et al. 2019). Mathematically, the optimization problems coined by Digital Twins of Manufacturing are so complex that direct optimization becomes computationally infeasible. A review of simulation optimization methods for stochastic simulation models is extensively reviewed by Xu et al. (2015). Some of the probably most promising ideas for this task include the use of deep learning neural networks or metamodeling techniques. Deep learning models are computationally heavy models that seem to be able to generalize solutions based on complex dynamic data without the need for handcrafted mathematical solutions (see, e.g., Silver et al. 2016). The idea of metamodels is to generalize data patterns into lower-level regression models to reduce the computational time required and generalize the system behavior on a high level (see, e.g., Burrows et al. 2011; Kuhlmann et al. 2005; Rupnik, Kukar, and Krisper 2007). It provides a computationally light way to optimize the underlying complex system. For a systematic and comprehensive review of metamodels, the reader is referred to Wang and Shan (2006).

As a summary of the literature, there is a strong need for further works of both theoretical and empirical nature, which can expand the research field on the managerial implications of digital twins in manufacturing systems. Summarizing the brief existent literature, though, it lends support to one of the notions behind this article, which is that optimized business investments in digital twins reflect shortcomings of current technology and other important situational contexts.

4 SIMULATION-BASED DIGITAL TWIN OF MANUFACTURING SYSTEMS - PREMISES OF IMPLEMENTATION

In the previous chapters, the definition of the simulation-based digital twin was provided which was followed by a literature study that verified the scarcity of contributions on the actual applications. Based on the theoretical framework, the surveyed literature, and previous hands-on experience in industrial projects, ten generalized propositions are proposed for consideration in the practical implementation of a simulation-based digital twin of a manufacturing system with complex behavior. While general, the propositions apply only to this specific type of Digital Twin and should not be generalized "as-is" to other types of DTs. The ten propositions are ordered by ontological, managerial, and technical-organizational considerations. The real-life sequential relationship between the propositions is shown and discussed in the results chapter.

Ontological considerations

PROPOSITION 1: The scale, scope, and detail level of collected data should match or exceed the data needs of the digital twin.

Ashby (1958) wrote about the concept of *requisite variety,* which is interpreted here as an imperative not to model an output that is dependent on inputs that the model does not contain. This **proposition 1** is self-evident but often neglected. If there is a managerial desire to build a high-detail, real-time digital twin model, the physical world should be equipped with adequate data-gathering equipment. It should be noted though that not all possible data has to be gathered, as the fidelity of simulation is dependent on its purpose (see, e.g., Madni, Madni, and Lucero, 2019). Capturing excessive data is not only suboptimal use of resources but unnecessarily stretches the cognitive ergonomics of users and managers by miring them in detail (Müller et al., 2018; Tao and Qi, 2019).

Persson (2002) reminds that by definition, a model is always some kind of abstraction of reality, and there is a trade-off between including as little as possible data, and at the same time maximizing the number of insights that can be gained. In the case of a manufacturing system with several inter-connected processes sampling their data with the uneven level of detail (number of dimensions), and uneven frequencies, the simplest and most scientifically sound solution is to take the highest level of data aggregation in the system-level simulation to avoid filling out the blanks. Wright and Davidson (2020) speak about the *sufficiency* of model characteristics concerning its envisioned use.

The concept of sufficiency is seemingly contradictory as, in the context of manufacturing, the most important operational leverage of DTs is expected to originate from the simulation of separate, high detail, digital twin entities (DTEs) in a high-frequency simulation. In practice, many situations exist with the need for an accurate simulation of some parts of the process in real-time, whereas some other variables remaining constant for long periods. Therefore, the value of information timeliness is in no way equal between processes, and, in a theoretical setting, having everything tracked online would be a serious waste of resources. As Stark et al. (2017) write that a complex CPPS (i.e. digital twin) needs abstracted behavior models and sub-systems to keep the computation time reasonable. West and Blackburn (2017) add that the separate modules should be self-contained with a minimal amount of coupling with the others. **Proposition 2** provides the summary of these observations:

PROPOSITION 2: The structure of the digital twin should be modular to allow dynamic adjustment in the level of granularity of individual processes

This **proposition 2** is often neglected in the literature. A recent meta-review by Jones et al. (2020) notes that only three out of 92 examined papers suggests that levels of fidelity should reflect its use case, even if there is little logical reason to believe a priori that equal levels of fidelity and granularity through the entire model is the resource-optimized best solution. However, one of the original visions behind the development of digital twins was to include all information useful in different lifecycle phases of a component, product, or system (Boschert and Rosen, 2016). Therefore, it is of importance that a DT-system, while being modular, should contain the element of traceability. Furthermore, as Erkoyuncu et al. (2020) note, an asset itself evolves over its lifecycle through modifications, so DT software must be able to both manage changes in data, and new software later included in the digital twin over the asset evolution must be able to manage existing data and add new. Zhang et al. (2019a), (2019b) draw attention to the possibility of a digital twin to aid reconfigurable manufacturing. This leads to **proposition 3:**

PROPOSITION 3: Digital twin of manufacturing should be an adaptive system with version history designed to support continuous modifications

In the case of continuous processes handling masses of substances, the future behavior of the downstream process depends on the preceding process phase(s) and – depending on the industry – time lags can easily reach minutes to days when some intermediate products are stored along the way. The time window to steer the production processes based on data can be long and small changes in the control variables have only insignificant, or non-observable, effects on the process outcomes. Therefore, as a general rule, the potential value added from system-level digital twinning has an inverse relationship with the batch size of a (continuous) process and its associated time lags. This observation is written in **proposition 4**:

PROPOSITION 4: The overall level of granularity in the digital twin of manufacturing tends to decrease as the scale of individual unit processes increases.

The latency issue is also identified by Lu et al. (2020), but they see it as more of an issue of standardization rather than a philosophical one. While the recommendation of a ‘designed for latency’ architecture is commendable, the issue requires a more fundamental rethinking of the construction of digital twins for MFS with respect to the time domain. A practical case example of a high-frequency DT-application in Redelinghuys et al. (2019) shows that even millisecond differences between databases can pose a problem for coordinated robotic functions.

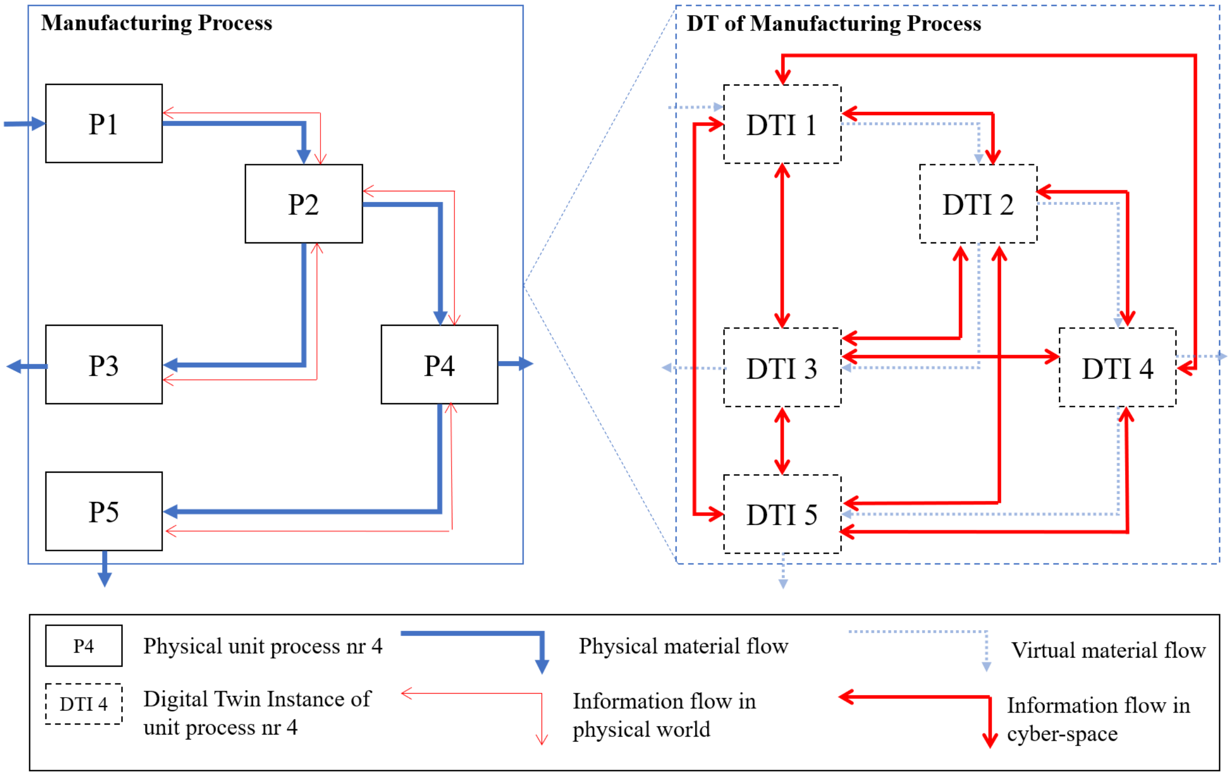

Figure 2. An illustration of the manufacturing process containing several unit processes (Pn; on left) converted into unit process-specific digital twin instances (DTIn).

In the physical manufacturing processes, the data exchange is mainly between separate sets of unit processes (see **Figure 2 left**) using crisp, single, number information (e.g. conveyer belt motor on/off, storage level below a threshold, etc.). In the virtual space each digital twin instance (DTI) represents its counterpart in the physical reality (see discussion, e.g., Yuqian Lu et al. 2020). To allow coordinated action (**Figure 2 right**), the information should flow seamlessly between separate DTIs within the full set of equipment. Moreover, the information content should not be limited to a single number on status, but the current, past, and probable future statuses of each DTI. These considerations are summarized in **proposition 5**.

PROPOSITION 5: The optimization of manufacturing processes using digital twin technology needs full-fledged cyber-cyber-communication between individual DT-components

In the context of system-level DTs, “real-time” becomes a relative concept: the downstream equipment uses the historical output of the upstream process equipment. The probable future statuses of individual downstream DTIs are estimated using a simulation of the historical output of the upstream. The efficient cyber-cyber communication and anticipation models ensure that the other entities (in process downstream or upstream) are properly configured for the optimal final product. In other words, optimizing individual equipment with machine-specific greedy algorithms (i.e. maximize the value of the next action) would easily lead to non-optimal results in subsequent processing. For optimal use of digital twins, developing this aspect of co-simulation between the DTIs is critical (cf. Talkhestani et al. 2019).

Managerial considerations

The key question from the managerial point of view that a simulation-based digital twin of manufacturing would strive to answer, is how to align all aspects of production planning to support the maximum number of company goals instead of achieving only local optima of performance (see also Kunath and Winkler (2018)). When detailed models of unit processes are available, the discipline of production engineering science has traditionally used Discrete Event Simulation (DES) -based representations of individual production lines in a bottom-up manner. The downside has been that these models become extremely complex when it comes to applying them in plant-wide solutions (see, e.g., Lidberg, Pehrsson, and Frantzén (2018)). From the managerial point of view, this creates a temptation to shortcut the modeling process into a top-down approach by simplifying and aggregating individual DT-objects to gain fast insights: any detail work beyond some managerially set, subjective level of detail is seen as digging into rabbit holes. While the managers do not want to be mired in details, cf. Müller et al. (2018), this thinking misses the fact that the digital twin model cannot create the managerially-craved new value creation opportunities without first diving into the details of individual processes that are being applied (see also Persson (2002) for further discussion). It is known and often without saying that people can at one point in time optimize either the high-detail single equipment functions or the overall process on an aggregate level. The key counterintuitive, and super-human, the fact to understand here is that once connected to the constant data feed and simulation model(s), digital twins can do both in a single moment.

PROPOSITION 6: The highest value-added by digital twins originates from steering detail-level behavior of its components to produce optimized overall system behavior at any given point of operation

The above **proposition 6** may seem superficial nonsense after what was being said about the (dynamic) level of digital twin granularity in **proposition 2**. The point is that the role of digital twin entities is to produce a large amount of numerical data on the *lowest acceptable level of granularity* from which the insights are derived using mathematical methods. If the ability to generate these data is cut out from the design, the digital twin is be de-facto neutered from its ability to produce something that is not known already. On the flip side of the coin, when the DT "only" mirrors what is already known, it can be regarded as valid and it is verified: the verification & validation (V&V) -the process becomes increasingly harder as DTs complexity and intelligence of the proposed solutions grows. Therefore, the V&V process has to be supported by solid domain knowledge: if one does not know the basics of the physical world system behavior, they are unlikely to be revealed in a simplified virtual world presentation. **Proposition 7** highlights this.

PROPOSITION 7: Digital twin requires rigorous verification and validation process like any other type of computational model

Each manufacturing process is a case of its own. Some industrial processes have existed for centuries with a lot of accumulated knowledge, whereas others are still on the drawing table. The recent advances in Artificial Intelligence (AI) may seem phenomenal, but very much limited in simplified artificial worlds of games (e.g. AlphaGo reported by Silver et al. 2016). AI refers here to the application of machine learning algorithms to analyze the "raw" data into insights with little or any user intervention – the types of solutions are regularly used in scheduling problems already (see, e.g., Priore et al. (2018), (2006)). In an artificial game setting the set of possible next actions is limited and the damages because of false actions have no cost. False moves in a factory operation, on the other hand, can lead to damage of millions of dollars or even to the loss of lives without the possibility to reset the “playing board”. Thus, when it comes to the implementation of AI-based algorithms, still mostly tested in artificial game worlds, some manufacturing processes are realistically speaking in a much better position compared to others: the more repeated events and repeated patterns there are, the better the currently available AI-algorithms will work.

It is already observed (see, e.g. Madni, Madni, and Lucero (2019)) that the equipment suppliers may be the winners of digital twin technology. Having accumulated execution databases on several equipment installations, they may be better equipped to build and implement digital twin models compared to the owners of one or few individual manufacturing operations. From an investment perspective, this fits with the servitization logic of Qinglin Qi et al. (2018) suggesting that manufacturing owners should integrate a series of digital twins built elsewhere rather than constructing a unique system from scratch. This **proposition 8** can be considered as a caveat for the top-level policymakers who envision a future with portfolios of unique, custom-fit, operation-specific DTs.

PROPOSITION 8: Digital twin of manufacturing is most suitable for applications that consist of series of equipment performing repeating, high-frequency events with preferably small variance and a high number of variables

To take a system theoretical approach, digital twins might have been developed to mitigate "*unpredictable, undesirable emergent behavior in complex systems*" (Grieves and Vickers 2017). However, the digital twin of manufacturing is still today most suitable for *complicated* systems, i.e. systems, in which the parameters of the "input-process-output"-chain are known precisely. For the reasons described above, digital twins of single manufacturing processes or instances are easier to realize than system-level DTs – and the vision is both feasible and in operation today. The next frontier likely to be conquered is so-called "closed-loop" systems, such as the air cargo load planning operations described by Wong et al. (2020). For larger and technically more complex manufacturing systems, gaps remain between the digital twin vision and the limits of technology.

West and Blackburn (2017) highlight that as the complexity of models grow the role of sub-model coordination and interconnection increases exponentially leading to higher costs of model maintenance. This evident development towards ever-higher costs may make the decision-makers redundant to fund the initial development or keep the project on-going later (West and Blackburn, 2017). The lack of immediate payback coupled with the current technological limitations leads us to another proposition, **proposition 9**, that may again seem self-evident, but which should capture the attention of many companies considering their entrances in the digital twin-field.

PROPOSITION 9: The mere promise of potential future returns by digital twin technology should encourage investments towards cost-effective data collection and management, even if today the immediate benefit would be low

From the day-to-day managerial point of view, manufacturing companies' investments in digital twins should be chosen based on a fit-for-purpose today, not based on the possible realization of a vision several years from now. However, investments in digital twins are more likely to profit the better the data available is. Therefore, as of today, managers should consider whether dedicated investments in demonstrations and DTs of closed parts of manufacturing systems, may cost-effectively be combined with the enhanced collection of other, related data that is potentially valuable in the future. The important thing will be to prioritize the most important data streams and avoid data streams most likely to be obsolete before utilization is applicable.

Technical and organizational considerations

Today, there are only a few dedicated software platforms for building digital twins (Yuqian Lu et al., 2020), but taking into account the complexity and variety of manufacturing systems, it is questionable whether any of this software ever becomes a "one size fits all" -type of solution. The ideal software platform should automatically solve the above-described issues such as the data gathering (with cleaning and merging), providing a semantic data-based interface that is both intuitive and has built-in virtual modularity that allows putting together DTIs of different types and granularity for parallel simulation. Also, having acknowledged the heaviness of simulation optimization, discussed in Xu et al. (2015), the software platform should provide a natural integration to cloud computing to easily parallelize (parts of) the overall system simulation. According to the review of Jung et al. (2018), there are currently no co-simulation approaches that would natively allow building intelligence on top of several simulation models running in parallel.

The type of IT-infrastructure with multiple data processing/simulation phases has to be, in practice, some kind of a software pipeline with several dedicated expert-software packages. This approach tends to grow and, most importantly, in the complexity of implementation. Jung et al. (2018) provide a practical example of such construction with the description of key issues when co-simulating separate digital entities in a (near) real-time environment. These considerations are summarized in **proposition 10**.

PROPOSITION 10: Digital twin of the manufacturing system will be an application-specific, virtual construction with several software components that maximally exploit the already existing IT-infrastructure and not replacing it unnecessarily

Madni et al. (2019) summarize the cost of a digital twin to be dependent on its scale, scope, purpose, and complexity, while Cimino et al. (2019) express their concern about the scalability and technological robustness of digital twins. West and Blackburn (2017a) evaluate the cost of implementing an aerospace digital twin with real-time capabilities concluding that the effort of this scale would require hundreds of millions of dollars with thousands of programmers in a 10-year project timeframe. The ability to connect between physical and virtual worlds is a topic that remains a topic of discussion in the literature (see, e.g., Schroeder et al. (2016)).

The modern manufacturing environment, in principle, already does provide an excellent basis for building simulation-based digital twins. First, a key enabling technology of DTs is, evidently, the increased amount of sensors and online measuring equipment (Zhang et al., 2017). Second, several information systems exist in a time-tested IT-infrastructure (such as SQL and equiv.), where the digital twin can and should connect. Some of the information systems include (see, e.g., Min et al. 2019): DCS, Manufacturing Execution System (MES), Laboratory Information System, and Enterprise Resource Planning (ERP). Assuming an existing manufacturing plant with a (near) real-time DCS in place, one can ask what is the value-added from building a new “DT-dedicated IT-infrastructure” partly serving the needs that are already met. By gradually building and implementing “DT-type of capabilities” on top of what already exists is also the way to keep the organization informed on what is being done and why. DT-systems that exist outside the existing IT-systems will be obsolete sooner than the research paper describing the system is published.

5 APPLICATION OF THE PROPOSED DIGITAL TWIN FRAMEWORK

This chapter provides an application framework for the 10 propositions (**Figure 4)**. It is purposefully generic, which conforms to the nature of this paper. In real case examples, the framework is best applicable for industrial operations with large-scale (high production volumes with large capital requirement), but narrow scope (relatively small number of final products). These processes operate with continuous/semi-continuous processes using multiple pieces of equipment with a relatively fixed configuration in a single production line, and therefore the benefits of seamless, automated, co-operation of equipment become possible, and monetary benefits are large even from small improvements. The main reasons why one should today (as of May 2021) focus on large-scale operations are the availability of data (technical potentiality) and the likelihood of a reasonable payback (managerial motivation) that were addressed in vast in this research. Such industrial process examples can include but are not limited to, chemical refineries (e.g. oil, concentrator plants in metals mining) and wood-based products context (e.g., sawmills, paper mills, veneer production).

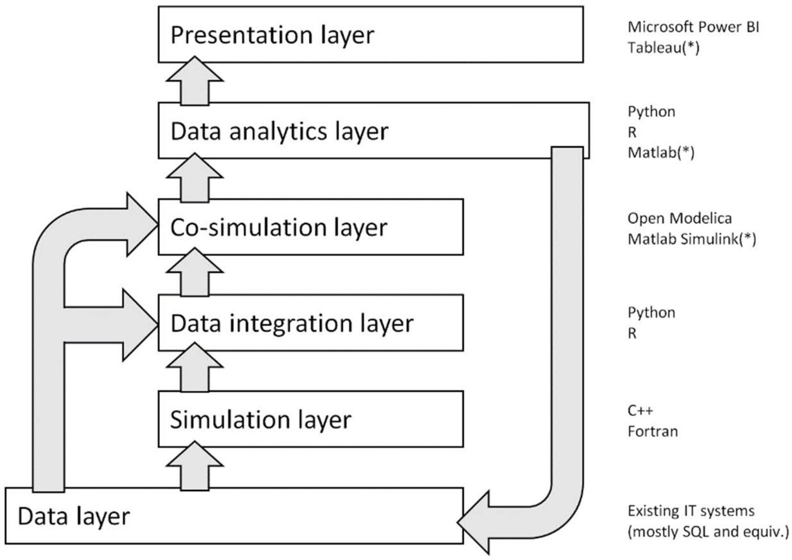

Figure 3. The proposed application framework of the system-level digital twin. The arrows represent the flow of data. On the right, possible software/programming language solutions are provided with a preference to freely available alternatives. Asterix (*) indicates commercial software packages.

As stated in **proposition 1**, the digital twin building starts with the availability and quality of the data, which is labeled as the *Data layer* in **Figure 4**. The databases to connect should be preferably the ones existing already inside the organization (**proposition 10**) and they should be selected based on the actual needs of the DT-model.

There should be a minimum amount of software lock-ins of the system definitions. This is enabled, when the DT model is made in a piecewise, granular fashion with adequate version control, where the database connections can be added/removed flexibly (**proposition 2, 3 and 9**).

The *simulation layer* includes different equipment-specific models that are used to optimize their behavior. Often, these models are physics-based, discrete simulations that have been written decades ago and copyrighted by the original equipment manufacturer (OEM) ever since. From the overall DT granularity point of view, it is probably beneficial to include the resulting numbers of such models as data inputs. The *data integration layer* does the heavy lifting on data pre-processing (e.g. re-naming, joining, merging, categorization, and so forth). If the data flow is a physical measurement of the process in an appropriate format, which might be the case with non-legacy equipment, then the data feed might be directly fed into the next phase (*co-simulation layer*). Commercial software with graphical interfaces available to do some of the basic operations for data pre-processing, but in practice, the most flexible solutions can be constructed and implemented via modern scripting languages such as Python. Because of the laborious construction and implementation of the *data integration layer*, it is of essence not to undertake a mega-sized digital twin building effort without thorough initial planning on what is being done and which data is needed (**proposition 4**). Ideally, the initial planning should be supported by a proof of concept tests for the envisioned IT-infrastructure/software pipeline using a small sample of data with only some tens of data measurements or data inputs.

The *co-simulation layer* brings together the data feeds needed for the system-level simulation. Co-simulation may include a mirror-like digital image of the real process[1], but more likely it is a flowsheet of dynamic simulation (e.g. in *Open Modelica* or *Matlab Simulink*) that can be constructed and linked to underlying data. Within this dynamic system model, the individual parts of the process come together as a linked entity once their connections are established (see, **proposition 5** regarding cyber-cyber - communication of DT-components).

Following the diagram in **Figure 4**, the *data analytics layer* is the place where the magic of data analytics happens that is the optimal state of the system components at any given moment is calculated (**proposition 6)**. One important notation, and an essential requirement for system-level simulation front-run, is the ability to feedback the results gained from the *data analytics layer* back to the *data layer* at the bottom as shown in **Figure 4**. That is, the feedback loop contains the arrays of optimized system parameters that are calculated or forecasted in each iteration of the system-level DT. As trivial as it may seem on paper, creating a feedback loop from the system-level DT back to the process control software through firewalls can be a technically daunting task which, again, is one of the key managerial reasons for starting small in the system-level DT-projects (see, also **proposition 10**). Secondly, it is much easier to keep a system model verified and validated when components and/or their functionalities are added gradually (**proposition 7**).

System output data (simulation/actual/forecast) produced by the *co-simulation layer* is usually so large, it is required that suitable machine learning (ML) algorithms are

[1] If CAD-drawings and resources are available, it might be a good idea to spice up the simulation model presentation with 3D-visualization tools such as Unity 3D for digital imaging of the process. However, the value of these flowsheet visualizations may be more in “selling” the digital twin inside the organization rather than creating managerial and economic value (see also cf. West et al., 2021).

used that regress and classify the data into meaningful insights (see discussion related to **proposition 8**). The role of algorithm-based analytics should not be exaggerated; instead, it is advisable to use as little as possible algorithmic processing (i.e. estimation) of the co-simulation data here as it is another source of possible errors and a place of constant maintenance from the system point of view. The reality, however, is that the more data and complexity there is, the more likely is the need for ML-based analysis. As the ML-algorithms have a constant hunger for more data, rather than less data, the **proposition 9** holds.

Lastly, the *presentation layer* displays the results of interests. The key problem with presenting what the MFS DT is doing, why and how is the dimensionality of data which can partly be addressed by modern software (such as *MS Power BI* or *Tableau*). To keep the presentation simple, one should focus first on mirroring the measures (key performance indicators) that are already being monitored by the human operators and, when needed, there should be a separate dashboard on the tasks that the DT is specifically set to do and optimize.

This chapter has shown a tangible, yet generic, version of the system-level digital twin concept proposed in this paper which is essentially "only" a clever software pipeline with seamless connection to the digital process data as discussed in the body of this paper. To encourage future research around the topic as well as entrepreneurship (or organizational intrapreneurship as well), the software packages mentioned were intentionally selected to be freeware which allows one to bootstrap manufacturing system-level digital twin that concurs with the propositions given and is, thus, implementable in practice.

6 RESULTS

Summarily, the ten propositions sought to address the aspects of digital twins that arise from the added level of complexity present in smart manufacturing systems and the ideas were further explained using a generic application example. Considering the current stage of DT-technology, it might be an important step forward for aligning digital twin models with management visions to create more “human-friendly” tools (as suggested by Yuqian Lu and Xu (2018)). However, a more critical and realistic way forward is also to understand the variation between management vision and digital twin reality - and to use the latter as a basis for construction and investment considerations. This, to paraphrase the Gartner Hype Cycle cf. Wright and Davidson (2020), will move digital twin models from the ‘trough of disillusionment’ to a ‘plateau of productivity’.

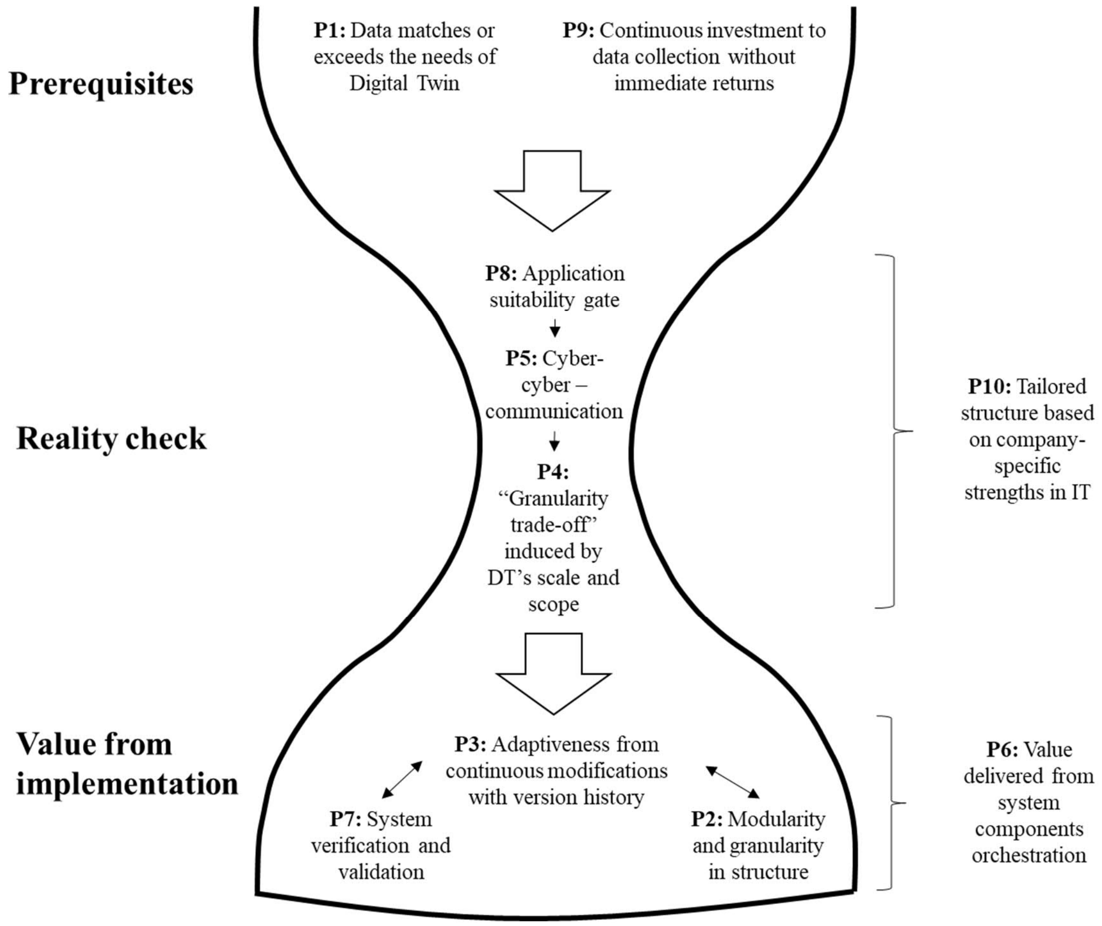

Figure 4. The relationship between the ten propositions

To simplify the central message of the ten propositions there is a bottleneck from the current state of having (most of the) data to a state of building fully functional system-level DTs that are of managerial value. The key bottlenecks, as illustrated in the **Figure 4** hourglass, are related to finding (the most suitable) applications that are within the reach of the technology (simple) while still have complex behavior pattern(s) that, when controlled as a system of interactions, yield monetary value. To elaborate this thought further, the managerial idea of Digital Twin today, whether explicitly stated or not, often seems to remain a 3D-animated version of his/her master spreadsheet with manual input from several data sources. The power of animation should not be underestimated, but as a simple analogy, what a manager sees in these "trade fair -compatible" representations could be usually regarded as useful as looking at a low-resolution photograph of a flow of traffic on a busy highway and trying to answer the question about the average speed of vehicles and the number of passengers per hour. Driving a car on this very same highway would have about as much predictive power for the system, although the driver would be able to give status information (e.g. speed) that reflects the status of other cars as well. The actual, beneficial role of the digital twin of manufacturing would be to simultaneously combine the aspects of the external observer and the driver of a single car into economically valuable and predictive insights.

Table 2. Summary of managerial topics to be considered when starting a project to produce a simulation-based digital twin of manufacturing.

Issue of managerial consideration	**Propositions**
The industrial setting in question provides adequate data that allows the DT to be built in a modular fashion with dynamic granularity	[1…4]
Solid domain knowledge is available on the individual parts of the system and their mutual interactions	[4…7]
The potential to produce economic value exists far beyond (initial) costs	[6…9]
DT is built on the strengths of current IT-architectural solutions in the organization	[8…10]

The managerial takeaway of this paper is to realize the vast range of issues (summarized in **table 2**) associated with the digital twin modeling of manufacturing systems. For complex manufacturing systems, the vision seems not yet attainable, and foregoing more realistic propositions can lead to major misguided investments in the coming years. As discussed in Xu et al. (2015) in the setting of simulation optimization of stochastic systems (i.e. resolving the states of the MFS in question), it is impossible to give an optimal solution with certainty within a limited amount of time and available data. Data availability is limited because, as discussed related to **proposition 9**, there is a little managerial incentive for paying for extra data collection that *might* be usable in the future, *if* digital twin makes it a final breakthrough. Moreover, the data collected have its due date as the processes are continuously evolving. Therefore, attempting to build overly complex DTs is likely to lead to a bitter failure and possibly neglect the long-term potential of Digital Twins as a technology.

As a word of encouragement, one should still leverage the managerial ideas of starting with profitable and workable “low-fidelity” DTs with limited data collection and uses to create practically viable platforms. Demonstrations even within *certain closed parts* of manufacturing systems could speed up the in-house and industry-wide development of DTs towards the ideal technology visions.

Yet, an unseen question of the future may be whether the management would be ready to take the risk of failure in technology implementation if ideally, world-mimicking DTs start to emerge in numbers that produce optimization solutions exceeding human reasoning.

7 CONCLUSIONS

Smart manufacturing is a vision of next-generation manufacturing built on emerging information and communication technologies (Yan Lu et al., 2016) where digital twins are a central component. Today, manufacturing systems may not yet fully embody these visions; rather the ontological and technological basis on how to build system-level DTs can be debated together with its managerial rationale.

As a key contribution of this paper, the key issues of applying digital twin technology into manufacturing systems were formalized into ten generic propositions based on the synthesis of the existing scientific knowledge. The list provided should be seen as a guideline and as a reality check when considering to initiate a project to construct a simulation-based digital twin of a manufacturing system: if warning flags are raised, then one should reconsider whether the project is worth undertaking or should it be downsized to a more focused effort. The propositions of the paper suggest that for the foreseeable future industrial investments in digital twins for controlled processes and closed parts of manufacturing systems are more likely to carry a positive economic impact than costly investments in *visionary* system-wide deployments. A generic framework and the related example provided in the article exemplify how the propositions can be taken into consideration in practical cases.

The literature study included in the paper revealed how little is actually known about managerial aspects of digital twins for manufacturing systems. Despite the major growth in interest for digital twins also in the academic world, only a few research publications deal with these issues. More research will also be needed to reflect the practical case examples of adoptions of digital twins in the industry that should be supported by a thorough, analytical literature review on the reported existing DT-applications. It might be also beneficial to collect the experiences of managers, model builders, and - operators, with respect to the ten propositions laid out in this paper. This approach could be helpful when steering digital twin -technology development from a hyped-up vision towards being a stable industrial reality.

Funding

This work was supported by the Strategic Research Council (SRC) at the Academy of Finland through the Manufacturing 4.0-project [grant numbers 313349, 313396, 313395].

Declaration of interest statements

The authors declare that there is no conflict of interest.

References

Alam, K. M., and Saddik, A. El. (2017). C2PS: A Digital Twin Architecture Reference Model for the Cloud-Based Cyber-Physical Systems. *IEEE Access*, *5*, 2050–2062. https://doi.org/10.1109/ACCESS.2017.2657006

Ashby, W. (1958). Requisite variety and its implications for the control of complex systems. *Cybernetica*, *1:2*, 83–99. http://pcp.vub.ac.be/Books/AshbyReqVar.pdf

Ayani, M., Ganebäck, M., and Ng, A. H. C. (2018). Digital Twin: Applying emulation for machine reconditioning. *Procedia CIRP*, *72*, 243–248. https://doi.org/https://doi.org/10.1016/j.procir.2018.03.139

Bao, J., Guo, D., Li, J., and Zhang, J. (2019). The modelling and operations for the digital twin in the context of manufacturing. *Enterprise Information Systems*, *13*(4), 534–556. https://doi.org/10.1080/17517575.2018.1526324

Bevilacqua, M., Bottani, E., Ciarapica, F. E., Costantino, F., Donato, L. Di, Ferraro, A., Mazzuto, G., Monteriù, A., Nardini, G., Ortenzi, M., Paroncini, M., Pirozzi, M., Prist, M., Quatrini, E., Tronci, M., and Vignali, G. (2020). Digital twin reference model development to prevent operators' risk in process plants. *Sustainability (Switzerland)*. https://doi.org/10.3390/su12031088

Boschert, S., and Rosen, R. (2016). Digital Twin—The Simulation Aspect. In *Mechatronic Futures*. https://doi.org/10.1007/978-3-319-32156-1_5

Burrows, S., Stein, B., Frochte, J., Wiesner, D., and Műller, K. (2011). Simulation Data Mining for Supporting Bridge Design. In P. Vamplew, A. Stranieri, K.-L. Ong, C. Christen, & P. J. Kennedy (Eds.), *AusDM '11 Proceedings of the Ninth Australasian Data Mining Conference - Volume 121* (pp. 163–170). Australian Computer Society, Inc., Darlinghurst, Australia, Australia.

Cheng, Y., Zhang, Y., Ji, P., Xu, W., Zhou, Z., and Tao, F. (2018). Cyber-physical integration for moving digital factories forward towards smart manufacturing: a survey. *International Journal of Advanced Manufacturing Technology*. https://doi.org/10.1007/s00170-018-2001-2

Ciano, M. P., Pozzi, R., Rossi, T., and Strozzi, F. (2020). Digital twin-enabled smart industrial systems: a bibliometric review. *International Journal of Computer Integrated Manufacturing*. https://doi.org/10.1080/0951192X.2020.1852600

Cimino, C., Negri, E., and Fumagalli, L. (2019). Review of digital twin applications in manufacturing. *Computers in Industry, 113*, 103130. https://doi.org/https://doi.org/10.1016/j.compind.2019.103130

Erkoyuncu, J. A., del Amo, I. F., Ariansyah, D., Bulka, D., Vrabič, R., and Roy, R. (2020). A design framework for adaptive digital twins. *CIRP Annals*. https://doi.org/10.1016/j.cirp.2020.04.086

Errandonea, I., Beltrán, S., and Arrizabalaga, S. (2020). Digital Twin for maintenance: A literature review. In *Computers in Industry*. https://doi.org/10.1016/j.compind.2020.103316

Gabor, T., Belzner, L., Kiermeier, M., Beck, M. T., and Neitz, A. (2016). A Simulation-Based Architecture for Smart Cyber-Physical Systems. *2016 IEEE International Conference on Autonomic Computing (ICAC)*, 374–379.

Grieves, M. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In F.-J. Kahlen, S. Flumerfelt, and A. Alves (Eds.), *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches* (pp. 85–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-38756-7_4

Grieves, M. W. (2019). Virtually Intelligent Product Systems: Digital and Physical Twins. In *Complex Systems Engineering: Theory and Practice*. https://doi.org/10.2514/5.9781624105654.0175.0200

Guo, J., Zhao, N., Sun, L., and Zhang, S. (2019). Modular based flexible digital twin for factory design. *Journal of Ambient Intelligence and Humanized Computing*. https://doi.org/10.1007/s12652-018-0953-6

Hu, J., Yin, J., Peng, Y., and Li, D. (2006). Knowledge Discovery from Multidisciplinary Simulation to Support Concurrent and Collaborative Design. *2006 10th International Conference on Computer Supported Cooperative Work in Design*, 1–6. https://doi.org/10.1109/CSCWD.2006.253177

Jones, D., Snider, C., Nassehi, A., Yon, J., and Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*. https://doi.org/10.1016/j.cirpj.2020.02.002

Jung, T., Shah, P., and Weyrich, M. (2018). Dynamic Co-Simulation of Internet-of-

Things-Components using a Multi-Agent-System. *Procedia CIRP*, *72*, 874–879. https://doi.org/https://doi.org/10.1016/j.procir.2018.03.084

Kemper, H.-G., Fettke, P., Feld, T., and Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, *4*, 239–242. https://doi.org/10.1007/s12599-014-0334-4

Kleijnen, J. P. C. (1979). Regresssion Metamodels for Generalizing Simulation Results. *IEEE Transactions on Systems, Man and Cybernetics*, *9*(2), 93–96.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., and Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022. https://doi.org/https://doi.org/10.1016/j.ifacol.2018.08.474

Kuhlmann, A., Vetter, R.-M., Lübbing, C., and Thole, C.-A. (2005). Data Mining on Crash Simulation Data. In P. Perner & A. Imiya (Eds.), *Machine Learning and Data Mining in Pattern Recognition* (pp. 558–569). Springer Berlin Heidelberg.

Kunath, M., and Winkler, H. (2018). Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process. *Procedia CIRP*, *72*, 225–231. https://doi.org/10.1016/j.procir.2018.03.192

Li, X., Cao, J., Liu, Z., and Luo, X. (2020). Sustainable business model based on digital twin platform network: The inspiration from haier's case study in China. *Sustainability (Switzerland)*. https://doi.org/10.3390/su12030936

Lidberg, S., Pehrsson, L., and Frantzén, M. (2018). Applying Aggregated Line Modeling Techniques to Optimize Real World Manufacturing Systems. *8th Swedish Production Symposium, SPS, Stockholm, Sweden May 16-18, 2018*, *25*, 89–96. https://doi.org/10.1016/j.promfg.2018.06.061

Liu, M., Fang, S., Dong, H., and Xu, C. (2020). Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems*. https://doi.org/10.1016/j.jmsy.2020.06.017

Liu, Q., Zhang, H., Leng, J., and Chen, X. (2019). Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system. In *International Journal of Production Research* (Vol. 57, Issue 12). Taylor & Francis. https://doi.org/10.1080/00207543.2018.1471243

Lu, Yan, Morris, K., and Frechette, S. (2016). Current Standards Landscape for Smart Manufacturing Systems. In *National Institute of Standards and Technology, NISTIR,*. https://doi.org/10.6028/NIST.IR.8107

Lu, Yuqian, Liu, C., Wang, K. I.-K., Huang, H., and Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing*, *61*, 101837. https://doi.org/https://doi.org/10.1016/j.rcim.2019.101837

Lu, Yuqian, and Xu, X. (2018). Resource virtualization: A core technology for developing cyber-physical production systems. *Journal of Manufacturing Systems*. https://doi.org/10.1016/j.jmsy.2018.05.003

Madni, M. A., Madni, C. C., and Lucero, D. S. (2019). Leveraging Digital Twin Technology in Model-Based Systems Engineering. In *Systems* (Vol. 7, Issue 1). https://doi.org/10.3390/systems7010007

Mei, L., and Thole, C. A. (2008). Data analysis for parallel car-crash simulation results and model optimization. *Simulation Modelling Practice and Theory*, *16*(3), 329–337. https://doi.org/https://doi.org/10.1016/j.simpat.2007.11.018

Min, Q., Lu, Y., Liu, Z., Su, C., and Wang, B. (2019). Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. *International Journal of Information Management*, *49*, 502–519. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.05.020

Müller, J. R., Panarotto, M., Malmqvist, J., and Isaksson, O. (2018). Lifecycle design and management of additive manufacturing technologies. *Procedia Manufacturing*. https://doi.org/10.1016/j.promfg.2018.01.019

Murphy, A., Taylor, C., Acheson, C., Butterfield, J., Jin, Y., Higgins, P., Collins, R., and Higgins, C. (2020). Representing financial data streams in digital simulations to support data flow design for a future Digital Twin. *Robotics and Computer-Integrated Manufacturing*. https://doi.org/10.1016/j.rcim.2019.101853

Negri, E., Fumagalli, L., and Macchi, M. (2017). A Review of the Roles of Digital Twin in CPS-based Production Systems. *Procedia Manufacturing*, *11*, 939–948. https://doi.org/https://doi.org/10.1016/j.promfg.2017.07.198

Persson, J. F. (2002). The impact of different levels of detail in manufacturing systems simulation models. *Robotics and Computer-Integrated Manufacturing*, *18*(3), 319–325. https://doi.org/https://doi.org/10.1016/S0736-5845(02)00024-8

Priore, P., de la Fuente, D., Puente, J., and Parreño, J. (2006). A comparison of machine-learning algorithms for dynamic scheduling of flexible manufacturing systems. *Engineering Applications of Artificial Intelligence*, *19*(3), 247–255. https://doi.org/https://doi.org/10.1016/j.engappai.2005.09.009

Priore, P., Ponte, B., Puente, J., and Gómez, A. (2018). Learning-based scheduling of flexible manufacturing systems using ensemble methods. *Computers & Industrial Engineering*, *126*, 282–291. https://doi.org/https://doi.org/10.1016/j.cie.2018.09.034

Qi, Q, and Tao, F. (2018). Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. *IEEE Access*, *6*, 3585–3593. https://doi.org/10.1109/ACCESS.2018.2793265

Qi, Qinglin, Tao, F., Zuo, Y., and Zhao, D. (2018). Digital Twin Service towards Smart Manufacturing. *Procedia CIRP*. https://doi.org/10.1016/j.procir.2018.03.103

Redelinghuys, A. J. H., Basson, A. H., and Kruger, K. (2019). A six-layer architecture for the digital twin: a manufacturing case study implementation. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-019-01516-6

Rosen, R., von Wichert, G., Lo, G., and Bettenhausen, K. D. (2015). About The Importance of Autonomy and Digital Twins for the Future of Manufacturing. *IFAC-PapersOnLine*, *48*(3), 567–572. https://doi.org/https://doi.org/10.1016/j.ifacol.2015.06.141

Rupnik, R., Kukar, M., and Krisper, M. (2007). Integrating data mining and decision support through data mining based decision support system. *Journal of Computer Information Systems*, *47*(3), 89–104.

Schroeder, G. N., Steinmetz, C., Pereira, C. E., and Espindola, D. B. (2016). Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange. *IFAC-PapersOnLine*, *49*(30), 12–17. https://doi.org/https://doi.org/10.1016/j.ifacol.2016.11.115

Shao, G., and Helu, M. (2020). Framework for a digital twin in manufacturing: Scope and requirements. *Manufacturing Letters*.

https://doi.org/10.1016/j.mfglet.2020.04.004

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., and Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, *529*(7587), 484–489. https://doi.org/10.1038/nature16961

Stark, R., Fresemann, C., and Lindow, K. (2019). Development and operation of Digital Twins for technical systems and services. *CIRP Annals*. https://doi.org/10.1016/j.cirp.2019.04.024

Stark, R., Kind, S., and Neumeyer, S. (2017). Innovations in digital modelling for next generation manufacturing system design. *CIRP Annals*, *66*(1), 169–172. https://doi.org/https://doi.org/10.1016/j.cirp.2017.04.045

Talkhestani, B. A., Jung, T., Lindemann, B., Sahlab, N., JAzdi, N., Schloegl, W., and Weyrich, M. (2019). An architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. *Automatisierungstechnik*, *67*(9), 762. https://doi.org/10.1515/auto-2019-0039

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., and Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology*, *94*(9), 3563–3576. https://doi.org/10.1007/s00170-017-0233-1

Tao, F., and Qi, Q. (2019). Make more digital twins. In *Nature*. https://doi.org/10.1038/d41586-019-02849-1

Tuegel, E. J., Ingraffea, A. R., Eason, T. G., and Spottswood, M. S. (2011). Reengineering Aircraft Structural Life Prediction Using a Digital Twin. *International Journal of Aerospace Engineering*, 14. https://doi.org/10.1155/2011/154798

Wagner, R., Schleich, B., Haefner, B., Kuhnle, A., Wartzack, S., and Lanza, G. (2019). Challenges and potentials of digital twins and industry 4.0 in product design and production for high performance products. *Procedia CIRP*. https://doi.org/10.1016/j.procir.2019.04.219

Wang, G. G., and Shan, S. (2006). Review of Metamodeling Techniques in Support of Engineering Design Optimization. *Journal of Mechanical Design*, *129*(4), 370–380. https://doi.org/10.1115/1.2429697

Wang, G., Zhang, G., Guo, X., and Zhang, Y. (2021). Digital twin-driven service model and optimal allocation of manufacturing resources in shared manufacturing. *Journal of Manufacturing Systems*, *59*, 165–179. https://doi.org/https://doi.org/10.1016/j.jmsy.2021.02.008

Waschull, S., Wortmann, J. C., and Bokhorst, J. A. C. (2018). Manufacturing execution systems: The next level of automated control or of shop-floor support? *IFIP Advances in Information and Communication Technology*. https://doi.org/10.1007/978-3-319-99707-0_48

West, S., Stoll, O., Meierhofer, J., and Züst, S. (2021). Digital Twin Providing New Opportunities for Value Co-Creation through Supporting Decision-Making. In *Applied Sciences* (Vol. 11, Issue 9). https://doi.org/10.3390/app11093750

West, T. D., and Blackburn, M. (2017). Is Digital Thread/Digital Twin Affordable? A Systemic Assessment of the Cost of DoD's Latest Manhattan Project. *Procedia Computer Science*, *114*, 47–56. https://doi.org/https://doi.org/10.1016/j.procs.2017.09.003

Wong, E. Y. C., Mo, D. Y., and So, S. (2020). Closed-loop digital twin system for air cargo load planning operations. *International Journal of Computer Integrated Manufacturing*. https://doi.org/10.1080/0951192X.2020.1775299

Wright, L., and Davidson, S. (2020). How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences*, *7*(1), 13. https://doi.org/10.1186/s40323-020-00147-4

Xu, J., Huang, E., Chen, C.-H., and Lee, L. H. (2015). Simulation Optimization: A Review and Exploration in the New Era of Cloud Computing and Big Data. *Asia-Pacific Journal of Operational Research*, *32*(3), 34.

Zhang, C., Xu, W., Liu, J., Liu, Z., Zhou, Z., and Pham, D. T. (2019a). A reconfigurable modeling approach for digital twin-based manufacturing system. *Procedia CIRP*. https://doi.org/10.1016/j.procir.2019.03.141

Zhang, C., Xu, W., Liu, J., Liu, Z., Zhou, Z., and Pham, D. T. (2019b). Digital twin-enabled reconfigurable modeling for smart manufacturing systems. *International Journal of Computer Integrated Manufacturing*. https://doi.org/10.1080/0951192X.2019.1699256

Zhang, H., Liu, Q., Chen, X., Zhang, D., and Leng, J. (2017). A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line. *IEEE Access*, *5*, 26901–26911. https://doi.org/10.1109/ACCESS.2017.2766453

Zheng, P., and Sivabalan, A. S. (2020). A generic tri-model-based approach for product-level digital twin development in a smart manufacturing environment. *Robotics and Computer-Integrated Manufacturing*. https://doi.org/10.1016/j.rcim.2020.101958

Zhidchenko, V., Malysheva, I., Handroos, H., and Kovartsev, A. (2018). Faster than real-time simulation of mobile crane dynamics using digital twin concept. *Journal of Physics: Conference Series*. https://doi.org/10.1088/1742-6596/1096/1/012071