Reviewing the Application of Data Driven Digital Twins in Manufacturing Systems: A Business and Management Perspective

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Abstract. Simulation modelling has been a widely used tool for analyzing manufacturing systems and improving their performance. Although, little attention has been paid to the application of data-driven simulation modelling of the manufacturing systems. With the development of new-generation information and digitalization technologies, more data can be collected from the manufacturing shop floor. This has paved the way for employing data-driven simulation of manufacturing systems knowns as a digital twin. This paper reviews the literature and practice on digital twins in manufacturing systems from a business and management perspective to identify the gaps and recommend avenues for future research. The results show that 2018 has been a turning point in the literature with small scale case studies of digital twins emerging independent of commercial practice. Since 2018 the digital twin literature has moved on from descriptions and conceptual frameworks to focus on one product lifecycle phase with any reference to sustainability advance being confined to energy and resource efficiency. Practice has been advanced by manufacturers and IT vendors however the definition of digital twins lacks precision for ease comparison with the literature. Future avenues for research are identified in the areas of lifecycle phases and digital model fidelity.

Keywords: Digital twin, Manufacturing systems, Production, Industry 4.0, Literature review.

1 Introduction

In today's highly competitive markets, increasing product variants and individualized demands are presenting new challenges to the manufacturing industry. Digitalization in manufacturing is seen as a promising solution to increase productivity and quality. The digital technologies also known as Industry 4.0 technologies enable real-time monitoring and control of intelligent components in the shopfloor by integrating and synchronizing the physical and virtual worlds [1]. The digital twin is one of the Industry 4.0 technologies that help optimize business performance.

The concept of the digital twin was first introduced by Grieves in an industry presentation in 2003 [2]. A digital twin is a virtual representation of a physical system developed as an independent entity. The digital twin contains the information embedded within the physical system and would have real-time communication with the physical system throughout its lifecycle [3]. Therefore, the digital twin provides crucial insights into the physical twin's performance, leading to actions such as a change in product design or manufacturing process design or control in the physical world.

Recent significant reductions in computing, storage and bandwidth costs have made data-driven technology such as digital twins economically feasible. Digital twin development provides cost saving and revenue generation opportunities for the companies across the lifecycle of their products and processes. For instance, reducing the time to market for a new product, reduced defects, cost saving opportunities and maintenance service business model opportunities for revenue generation. Such cost saving and revenue generation opportunities have attracted manufacturing companies to invest in digital twin technology. The digital twin market is forecasted to grow from its current market value of more than $4 billion to over $35 billion by 2026 [4].

Similar to the industry community, digital twins have drawn the attention of the academic community. The number of digital twin papers published in academic journals and conferences has risen significantly. Using a structured literature review, this paper discusses the concept and application of the digital twin in manufacturing systems. It provides a holistic overview of lifecycle phases in which a digital twin is implemented, modelling techniques applied, and solutions offered by vendors. This paper guides future work on the application of digital twins in manufacturing systems by identifying the gaps in the literature and contrasts with practice.

The paper is organized as follows. Section 2 presents the review methodology and a visualization of the literature. Section 3 classifies the literature based on publication type, lifecycle phases, research scope, and modelling techniques. Section 4 discusses the digital twin solutions offered by the digital twin vendors. Finally, a concluding discussion is presented in section 5.

2 Literature review methodology

A structured review was conducted to evaluate the body of literature on the application of digital twins in manufacturing systems from a business and management perspective. This systematic review was performed in accordance with the methodology presented by [5] and [6]. First, a search in Scopus was carried out to identify the relevant papers. The literature search was carried out using Boolean keywords combinations "(digital twin OR digital twins) AND (manufacturing OR manufacturing systems OR cyber physical production systems)". The search process led to 94 papers by limiting the search scope to the subject area 'Business, Management, and Accounting' and selecting papers in English published from 2018 until 2021. The reason for limiting the search to papers published from 2018 until 2021 is that Kritzinger et al. (2018) [7] and Negri et al. (2017) [1] have thoroughly reviewed the literature before 2018. The papers identified were reviewed and irrelevant ones excluded. The exclusion criteria were: (1) "digital twin" phrase is used without bidirectional data flow between the physical and digital entities; (2) Industry 4.0 technologies proposals for which digital twins is not the focus. This led to 55 papers for review.

2.1 Literature review analysis

The initial analysis was conducted to establish what keywords capture the field and-which journals and conferences are publishing such work.

A co-occurrence analysis of the literature using VOS viewer [8] identified keyword clusters. The results show industry 4.0, embedded systems, and cyber-physical systems are the most common keywords used in digital twin manufacturing systems papers.

International Journal of Production Research, IEEE International Conference on Industrial Engineering and Engineering Management, Journal of Cleaner Production, and International Conference Management of Large-Scale System Development are the top four contributors to digital twins in manufacturing systems literature. Operations research (OR) journals have not published studies on digital twins in manufacturing systems showing that OR techniques are in their infancy and more research is needed.

3 State of the art literature

In this section, the literature review on digital twins in manufacturing systems is classified by publication type, lifecycle phases, research scope, and modelling techniques.

3.1 Publication type classification

Kritzinger et al. (2018) [7] reported that the majority of the studies published between 2014 and 2017 focused on developing the conceptual frameworks. Since then, case studies represent 55% of works, outstripping conceptual frameworks at 41% and dwarfing review papers at 4%. Most cases are from academic laboratories with limited research on physical implementations. Interestingly, Kritzinger et al. (2018) [7] reported that up to 2017 a few studies discussed the definition but since this review shows no studies, indicating a consensus on the definition of the digital twins has been reached hence focus is now on small scale applications.

3.2 Life-cycle phase classification

A physical twin's lifecycle is characterized by four phases: (1) Design phase that contains not just the product design but the process and plant design as well; (2) Manufacturing phase that comprises the production and relevant internal plant logistics; (3) Service phase that includes distribution, use, repair, and maintenance; (4) Retirement phase that refers to operations such as disassembling, remanufacturing, reusing, disposal [9].

Table 1 illustrates the share of different lifecycle phases in the literature on digital twins in manufacturing systems. A few studies in the literature examined more than one life cycle phase of the physical twins. In this case, the main studied life cycle phase was considered for classification. 16% of the reviewed papers studied digital twins in the design phase of the physical twin's lifecycle. In the design phase of the physical twin, the digital twin provides designers with complete digital footprints of products and processes, thereby shortening the design cycle and reducing rework cost.

As shown in Table 1, more than half of the studies in the literature are related to the manufacturing phase of the physical twin's lifecycle. In the manufacturing phase, digital twins provide real-time monitoring of the manufacturing process, therefore reducing the defects and improving resource efficiency. Many manufacturing applications such as identifying the optimal machine sequencing and production schedule [19], minimizing the geometrical deviations [21], process planning [27], and efficient energy and resource planning [24, 25] were reported.

The service phase is the second most studied lifecycle phase in the literature, more than the design phase. Here the digital twin enhances the performance of the physical twin by monitoring the real-time operating state and providing predictive maintenance and fault diagnosis [50, 51], representing the supply chain network in real-time to provide complete end-to-end visibility [6, 52, 53, 55, 56].

Table 1. Literature on digital twins for the lifecycle of manufacturing systems

Phase	Share	Refs	Business outcome
Design	16%	[10-17]	Reducing design cost, Reducing design cycle, Increasing the geometrical quality of final product, Improving product performance
Manufacturing	52%	[18-48]	Reducing production cost, Increasing production efficiency, Increasing quality and throughput, Reducing the geometrical deviations, Reducing mean throughput time, Increasing resource and energy efficiency
Service	29%	[6], [49-62]	Reducing maintenance cost, reducing bullwhip effect and ripple effect, Increasing supply chain resilience
Retirement	3%	[63, 64]	Reducing the uncertainty in remanufacturing process, Reducing electrical and electronics equipment waste

The retirement phase of the product lifecycle is the least studied phase in the literature. Here the digital twin supports the recovery and remanufacturing process [63, 64]. In cases where the physical twin is not suitable for remanufacturing, the digital twin supports less environmental impact on disposal.

3.3 Research scope classification

Digital twins are developed to represent a detailed visualization of parts of the life cycle of physical products and processes. One of the most common areas of study is planning and control problems. Manufacturing system digital twins enable an order-based and automated production planning and control system by real-time monitoring of the production shop floor. 18% of the reviewed papers studied the application of digital twins in the manufacturing environment in general rather than focusing on a particular area within manufacturing. Product and process design is the third most studied problem. These studies aimed to reduce the design cost and design cycle of the new and existing products using digital twin technology. 14% of the studies in the literature are related to applying digital twins for predictive maintenance and fault diagnosis. Supply chain planning is the fifth most studied problem in literature, these studies aim to increase the efficiency of the supply chains as well as increase the resilience to disruption. Only 7% of the reviewed papers applied digital twins to increase the efficiency of the energy and resource planning in manufacturing systems. Finally, recovery and remanufacturing of the retired products is the least studied problem in the literature, indicating there is significant potential for further work in this area.

3.4 Modelling techniques classification

Digital twins are simulation models built using the real-time or near real-time data received from their physical twins [47]. Therefore, simulation is the main pillar of building digital twins. 38% of the literature on digital twins developed simulation models to represent the physical twins in different phases of the lifecycle and predict the future status of the physical twins. 29% of the studies incorporated optimization into simulation models to transform the digital twins from predictive models to prescriptive models. 15% of the papers integrated simulation and data analytics in digital twin models. In these studies, the data collected from physical twins are firstly analyzed by data analytics techniques such as machine learning that provide predictive analytics and are then input into the simulation models. Applying the data analytics techniques reduces the computational burden on simulation models and therefore run time of this combination is less than that for simulation models alone. 18% of the studies in the literature incorporated optimization into integrated simulation and data analytics models to improve the performance of the physical twins.

3.5 Literature findings

Reviewing the literature on digital twins in manufacturing systems since 2018 reveals many gaps: (1) Much of the literature presents laboratory case studies. The literature lacks industrial cases to show the implementation of the digital twin in real-world manufacturing systems; (2) Much of the literature study digital twins in one life cycle phase of the physical twin. Few studies consider the more than one lifecycle of the physical twin, none considers the whole lifecycle; (3) Among the lifecycle phases of the physical twins, the retirement phase is the least studied phase. More studies on digital twins in the retirement phase are needed to address the challenges of the return cycle; (4) Sustainability is poorly addressed, only a few papers consider the narrow scope of energy and resource efficiency. The literature reviewed does not go beyond this; (5) Modellers develop high fidelity real-time data-based simulation models, however, there are computational burdens in identifying optimal manufacturing decisions. There is a lack of work on multi-level modelling to consider variation in fidelity; (6) Data analytics has potential for reducing the computational time of simulation-optimization (including for high fidelity models) however frameworks for this lack development for wider application; (7) A limited number of studies employed machine learning techniques and more research on their use in the various life cycle phases is needed; (8) Humans are one of the main resources in the manufacturing systems. There is limited research on considering humans in the digital twins of the manufacturing systems.

4 Digital twin software

The digital twin market is forecasted to grow at a compound annual growth rate of over 30% from 2021 to 2026 [4]. This market growth opportunity has attracted many companies to invest in developing digital twin solutions. The digital twin solutions can be classified into commercial solutions and cloud-based solutions.

The commercial solutions are provided by the manufacturers of IoT-connected industrial products to create a digital twin of the manufacturing assets, processes, and systems. General Electric, Dassault Systemes, Siemens, and Bosch are the key players in providing commercial solutions. The cloud-based solutions are provided by IT companies to create digital twins of the assets, places, processes and people. Microsoft, Oracle, and IBM are the key players in providing cloud-based solutions.

The competitive advantage of the commercial digital twin solutions offered by the industrial equipment manufacturers is the availability of the ready to use digital twins of industrial equipment. The competitive advantage of the cloud-based digital twin solutions offered by IT companies is the seamless integration of these solutions with other cloud-based services such as AI and analytics. Industrial equipment manufacturers and IT companies are collaborating to integrate the advantages of the commercial and cloud-based digital twin solutions. The partnership between IBM and Siemens is an example of such collaborations.

Reviewing practice on digital twins in manufacturing systems against the gaps found in the earlier literature review reveals: (1) The peer reviewed literature lags industry application; (2) Little can be discerned about the dominant application of digital twins (e.g. manufacturing, service, etc) and whether applications span across multiple stages of the lifecycle; (3) Vendors do not explicitly address the fidelity versus computation time found to be an issue in the academic literature; (4) The potential for and mechanism of data analytics to reduce computation burden are unclear; (5) There is little evidence of environmental sustainability as a potentially valuable focus as identified by the literature; (7) Finally, the use of the term digital twin is dominant in practice but it is unclear if applications compise a bidirectional data flow between physical and digital twins. This lack of definition and clarity of what is being reported on industry application makes comparison with the academic literature difficult.

5 Conclusions

This paper reviewed manufacturing system digital twins in literature and from vendors. It is clear that most academic work has been on conceptual frameworks or case studies to address planning problems in the manufacturing phase of the physical twins. Simulation modelling is the inseparable element of the digital twins but appears only as high-fidelity analysis with its associated computational burden. The literature shows computational time can be reduced through data analytics but there is an absence of guidance on appropriate model fidelity. The literature lacks studies on digital twins addressing problems across the physical twin lifecycle as well as considering sustainability challenges beyond energy and resource efficiency. Similarly, there is a lack of work on manufacturing systems for end of life products. Studies are needed that consider humans in the digital twins of manufacturing systems. The industrial equipment manufacturers and IT companies that are the main vendors of digital twin solutions are collaborating to enrich their digital twin solutions. The commercial solutions reported are ahead in application in practice, however, most of the above research challenges remain.

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