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Digital Twin Models in Industrial Operations: A Systematic Literature Review

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Abstract

A Digital Twin is one of the enabling technologies of Industry 4.0 that couples actual physical systems with corresponding virtual representation. Currently, the application of Digital Twin models has attracted the attention of many researchers with the focus of production, predictive maintenance, and after-sale services. However, its role in industrial operations particularly in production, predictive maintenance, and after-sales services lacks efforts to systematically review the state-of-the-art. Moreover, this review discusses some of the challenges in implementing DT models to extend its role in the aforementioned application domains. In this paper, a systematic literature review was conducted to assess the role of Digital Twin models in industrial operations and to identify challenges for realization. Twenty-five research studies that were published until the end of June 2019 were selected and analyzed in order to show the current state-of-the-art on the role of Digital Twin models in the industrial operations and challenges in the implementation. Review results underline that the majority of the studies have focused on the application of Digital Twins in the production sector followed by predictive maintenance and after-sales services. Many authors have discussed how to apply Digital Twin models without remarking their role in the aforementioned domains of industrial operations. This paper provides insights for different industrial sectors, practitioners, researchers and experts of the field on the specific roles of Digital Twin models and challenges of implementing these models in the areas of production, predictive maintenance, and after-sale services.

Keywords: Digital twin models; predictive maintenance; production; after-sale services; operations

1. Introduction

Nowadays, the role of Industry 4.0 and smart factories has attracted the attention of many researchers [1,2]. Digital Twin (DT) is one of the enabling technologies of Industry 4.0 and it couples the actual physical system with corresponding virtual representation using model, sensors, data and software to monitor and analyze data. DT is a living model of the system or physical asset that can continually adapt to operational changes based on the collected online data and information, to forecast the future of the corresponding physical twin. It is non-destructive testing initiated by the evolution of industry 4.0 [3]. With the support enabling technologies like multi-physics simulation, cloud service and machine learning [4], it allows uninterrupted adaption to the changes in the operations or environment. Importantly, it enhances visibility in machines, enables simulation of various conditions and used to connect with business processes to support financial decisions, supply chain activities, etc. Therefore, this technology plays a fundamental role in production optimization and maintenance during the manufacturing and after-sale services yielding the best business outcomes. Moreover, the digitalization of manufacturing systems is a promising way for companies to adapt to customer needs, increased uncertainties and resource

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costs [5].

Regardless of increasing interest in the application of DT in different industrial sectors, its role in the industrial operations particularly in production, predictive maintenance, and after-sale services is not clearly identified. Many studies have described how to apply Digital twin models without remarking their role in industrial operations. Thus, clear identification of its roles and challenges for the implementation in industrial operations is important to give insights to companies and practitioners on how it will improve their manufacturing and services.

In the recent period, many papers have been published on the different applications of DT models. Although these works of literature cover a wide range of such applications, this review will focus on the current research on the roles of DT models in three specific domains including production, predictive maintenance, and after-sales services. Moreover, relatively little heed has been paid to the use of DT models in after-sale services relative to others, which is also an essential phase of product life cycle management. The paper focuses on the review of the aforementioned application domains of DT, while analyzing the current state-of-the-art on the use of this model. In addition, the review discusses challenges in the real-case implementation of DT models. Therefore, this paper presents the issues associated with the current state-of-the-art on the role of DT models in industrial operations with a specific focus on the production, predictive maintenance, and after-sales services including common challenges of real-case implementation of this technology. The paper is organized as follows. Section 2 presents the research method used for the review. Section 3 reports the results and analysis of literature, while section 4 discusses the role of DT models in three application domains. Section 5 provides insights on the current challenges and future works for the implementation of DT models. Lastly, section 6 provides the conclusion of the work.

2. Method

This systematic literature review has followed a detailed step-by-step approach proposed by [6,7]. The objective of the search was to identify papers that showed the current role of DT models in industrial operations. The main question that is addressed within this contribution is: what is the current state-of-the-art on the role of DT models in industrial operations (production, predictive maintenance, and after-sale services) and challenges with implementation to extend its role?

The literature review was carried through the steps including identification of research databases and keywords definition, literature search and paper selection through specific exclusion criteria followed by analysis process and information extraction strategy.

2.1 Data sources

The main databases used for collecting the articles were Scopus and Web of Science. These databases are multi-disciplinary and well-established research platforms containing a wide variety of journals with updated information. The two databases were queried in June 2019. Reference lists of eligible papers were screened for further analysis meeting the inclusion criteria. Databases were searched using a combination of the key terms: 'digital twin models', 'predictive maintenance', 'production', 'after-sale services', and 'operations'.

2.2 Paper selection

The search for papers was restricted to the keywords, abstract and title of the articles published between 2016 and 2019. In addition, articles published in English were considered and checked for duplicates without restricting the journals. The selection has taken place using specific exclusion criteria based on the availability of full text, the association between DT and operations, and the priority and the main contribution of the paper.

2.3 Paper analysis

The paper classification was done based on criteria including journal distribution, year of publication, type of paper (article, conference, book chapter) and percentage of authors by geographical origin, contribution and research method, and the main focus of the application domain. Through this, it was possible to classify the papers analyzed and identify the state-of-the-art on the role of DT from an industrial operation point of view.

3. Results

As DT is young technology attracting the attention of many researchers, the search was focused on the years between 2016 and 2019. In the search, 513 papers have been found in the largest abstract and citation databases Scopus and Web of Science.

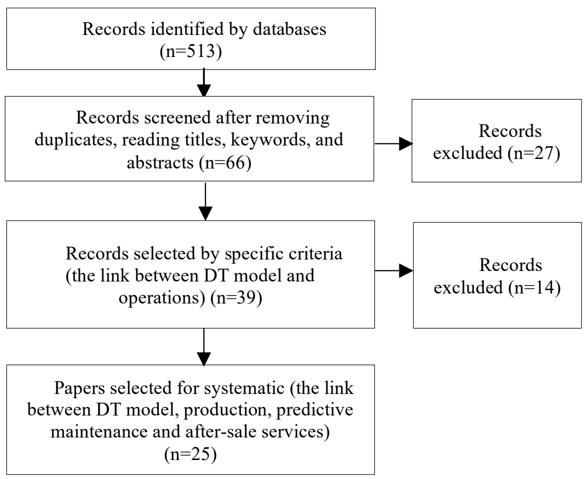

Figure 1. Paper selection process.

The search was conducted with terms: 'digital twin models' AND 'predictive maintenance', 'digital twin models' AND 'production', 'digital twin models' AND 'after-sale services' and 'digital twin models' AND 'operations'. After removing duplicates, initial screening was done based on the titles, keywords and abstract and 66 articles were selected. From this process, further 27 papers were excluded because the majority of the studies were focused on the development of the conceptual framework for DT models without mentioning its role in industrial operations. Therefore, the link between DT modeling and application in operations was strictly considered and 39 articles were screened out (Figure 1). Finally, the original sample of 39 articles was reduced into 25 based on the focus of the study on the role of using DT models more specifically, in production, predictive maintenance, and after-sales services. Thus, the total number of eligible studies used in the systematic review was 25.

As shown in Figure 2, 56% of selected papers are published in journals, 40% are conference proceedings and 4% are book chapters.

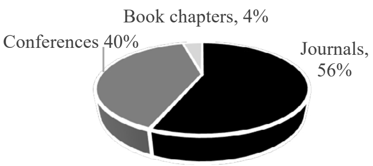

Figure 2. Editorial classification of selected papers

Table 1. Distribution of articles by the journal

Journal title	Number of articles
Procedia CIRP	7
Procedia manufacturing	6
IFAC-PapersOnLine	2
Journal of manufacturing systems	1
Computers & Industrial Engineering	1
CEIG - Spanish Computer Graphics Conference	1
Information fusion	1
International journal of information management	1
Academic Press	1
International conference on engineering design	1
Proceedings of the ASME 2016	1
CIRP Annals	1
AIP Conference Proceedings	1
Total	25

Table 1 reports the number of selected papers per journal. Accordingly, 28% of selected papers belong to the journal of Procedia CIRP, 24% of papers were published in Procedia Manufacturing and the rest of the papers belong to other categories.

According to Figure 4, the majority of the research comes from Germany followed by China, France, Spain, the USA, Sweden, Italy, Belgium, and other European and Asian countries.

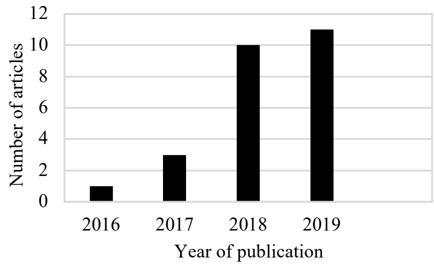

Figure 3. The distribution of articles by year of publication

In this field, Germany and China have contributed 46.5% of the study. Authors from Canada, Spain, Belgium, Italy, Netherlands, Portugal, New Zealand, France, Japan, Australia, Romania, Hungary, the USA, Sweden and South Korea contributed the rest of the studies.

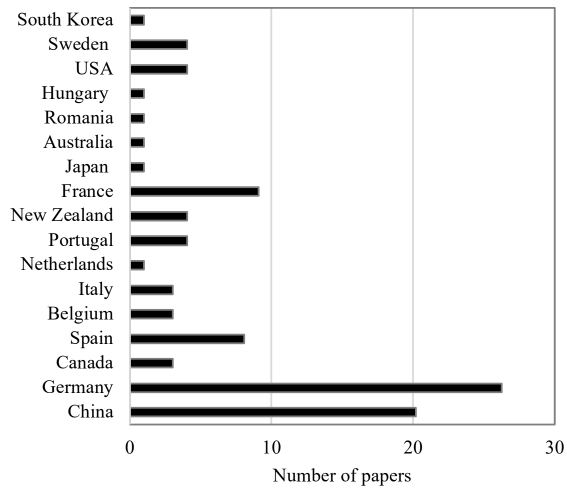

Figure 4. Percentage of authors by geographical origin

As shown in Figure 5, papers were classified based on the contribution and research methods. Thus, out of 25 selected papers, 8 of them have focused on framework development of DT applications, 7 papers on the development of methodology, 2 papers on the state of the art and the rest of papers have focused on different contributions.

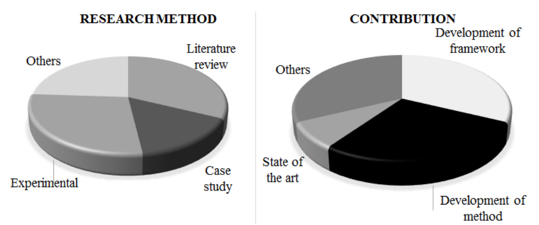

Figure 5. Classification of papers depending on the contribution and research method

On the other hand, based on the research methodology, 8 of the selected papers have assessed DT using a literature review, 4 papers have described the details of DT application with case studies, 4 papers have proved the use of DT models experimentally while the rest of the papers have used different methodology to prove the capability of DT models.

Figure 6. Distribution of papers based on the areas of application

Figure 6 shows the result of paper analysis based on the application domains. Accordingly, among the selected papers 40% [3,5,8,13,14,17,21–23,28] were focused on production, 28% [4,9,10,18,19,25,26] in predictive maintenance, 12% [11,15,20] in after-sale services and 20% [12,16,18,24,29] have given emphasis on different issues related to production, maintenance and services.

4. Discussions

DT is playing a great role in the operations throughout the product life cycle including product concept, product design, manufacturing planning, manufacturing execution, product sales, product usage, maintenance, and product renewal. Its role has extended to design, manufacturing and prognostics and health management [8,13,16] to optimize efficiency, speed up information flow and automation of the processes [12]. During the operation phase, the DT models can be used for the purposes of maintenance, increasing the speed of product tracking, or virtualization of certain conditions of the product during its operations [17]. This section discusses the role of the DT in industrial operations with special focus on the production, predictive maintenance, and after-sales services, as derived by review.

4.1. Digital Twin in production

DT is an important tool in the continuous improvement of the production system. Implementation of the DT concept can also open the way to use other digital technologies and innovations that successively improve the infrastructure for future business advancements. On the other hand, using what-if analysis DT enables the simulation of different scenarios to optimize the performance of the physical twin. Furthermore, it can enable visibility and transparency in the operations of the machines and other assets and interconnected systems. DT can also help to understand the behaviors of an individual machine and to integrate the system, which is important to achieve business outcomes within the framework of supply chain operations. In addition to the promotion of value and chains for the traditional business models, DT can also expand them to develop new value creation techniques through product-as-a-service business models, which improve the business ecosystem to contact new customers and other partners to create new opportunities. The role of DT is not limited to a specific area of the companies. It can also integrate the entire value chain to modify the business environment for products, communities, and services. This approach has been implemented as an innovative shop-floor management system in the Logistics Learning Factory [18]. On the other hand, digitalization can enhance the capability of small and medium-sized enterprises in data acquisition. The study has demonstrated the potentials uses and advantages of real-time data acquisition and subsequent simulation-based data processing in the production system [24].

A study [19] has evidenced the possibility of generating DT models for large production plants and factories to optimize working space layouts and improving safety, effectiveness, and ergonomics. Moreover, smart manufacturing has shown higher levels of automation, flexibility, and adaptability to changing material mixtures and values to support their operations [23, 31]. Therefore, digitalization is believed to be important in many aspects of industrial operations including increasing efficiency, reducing the cost and creating revenues through new products and product features as well as new businesses and business models [26]. Another study has proposed the application of a machine learning-based DT framework for production optimization in the petrochemical industry [14]. DT together with machine learning, the internet of things and data processing technologies play a great role in the transformation of traditional manufacturing paradigm toward smart manufacturing. This paradigm can potentially support manufacturing sectors by improving flexibility and levels of automation in many operations [31]. It is also considered as a key solution to improve digital monitoring systems and the function of interconnected devices of adaptive and more autonomous systems [21,22].

DT has been believed to be a key solution to improve the operations of many companies. Investigation revealed the integration of DT into manufacturing systems to solve the raising complexity of the order management process and to improve the flexibility and profitability of the companies [26]. Besides, this technology is considered as a new solution to enable on-going digital control and active functional advancement of interconnected products and machines. In addition, the introduction of DT can improve the vertical and horizontal integration of manufacturing systems [21]. This is a promising way for companies to adapt to customer needs, increased uncertainties and resource costs.

4.2 Digital Twin in predictive maintenance

Using different modeling techniques like simulation-based, data-based or mathematical modeling, the DT model can be utilized in the prediction of the future behavior of the assets and impacts due to disruptions. Therefore, as a living model, DT is important to identify potential problems with its real physical twin. This can allow the prediction of the remaining useful life of the physical twin combining physics-based models with data-driven analytics. Thus, using continuously acquired data with the industrial internet of things, DT can able to deliver accurate forecasting for specific predictive maintenance [9,10,20,26,27]. Therefore, DT can play a great role in early warning, prediction, and optimization of a manufacturing system or services by producing a mirror of the activities of a physical twin. In this area, the application of the DT model has become significant because many industries are moving from reactive to proactive maintenance to reduce operational downtime, maintenance costs, and capital investment. The studies [3,10] have described the role of DT technology in the operation of aircraft maintenance and the impact of technology advances and requirements on the conventional industry. However, researches on digital-based maintenances are at its infancy and still they have problems such as space limitation for the storage heterogeneous data, feedback on predicted results, etc. To solve this issue, a report [4] has proposed the application of deep learning for the tool system model to forecast the condition of system tools.

4.2. Role of Digital Twin in the after-sale services

The focus of many companies on after-sales services has been increased. After-sales service is able to generate around 80% of the company's profits [25]. Likewise, this enables companies to achieve their competitive advantages. However, in contrast to the important value of after-sale services, an insufficient amount of attention has been given to the application of DT in this sector.

After full implementation in a company, the DT of the product can be available from the phase of design to after-sale. In the after-sales, the use of DT allows the company to avoid sudden failure of something. It enhances the chance of tracking the overall performance and maintenance history of each physical replica in the time, detect and report abnormal behavior of the system, and recommend maintenance. Besides, the combination of DT models with services can improve manufacturing planning and production control [8]. Hence, the status of the product can be easily controlled using real-time data. Moreover, to ensure the satisfaction of customers DT enhances the permeability of documentation throughout the entire lifecycle of the product to provide traceability of product data management. This role has been demonstrated in order to improve the traceability of electric/electronic artifacts [15]. Incorporation of model-based systems engineering into product data management enhances the tracking capability of changes throughout the product lifecycle. Moreover, using digital platforms companies can improve operations through the interaction with their clients for customer support, to receive feedback about their product and services, to improve brand loyalty and to adapt to the needs of their consumers [12]. In a practical way, the application of DT models have been identified and described in smart farming in the context of potato harvesting to optimize the operation [11] then the general business model was validated by experts from agriculture and farmers to support decision-making.

5. Challenges and future works

Although DT is a key enabling technology of industry 4.0 to test new systems prior to manufacture, improve efficiency and productivity, forecast the future behavior of the system, and provide better service, still there are challenges regarding the use of these models in real cases. As part of Industry 4.0, developing methods for the application of DT models for industrial domains particularly production, predictive maintenance, and after-sales services is still at infancy. Many kinds of literature consist of papers with conceptual frameworks without concrete case studies and detailed methodologies. However, some applied case studies already exist in the literature [17]. Despite the fact that it is challenging, world top data processing companies are still working to develop and implement the DT models in real cases. Therefore, further research needs for real case studies in developing methods to implement DT in the industrial environments in order to enhance its possible roles in industrial operations. Regarding implementation, construction, understanding, and control of the machine with an accurate multiscale DT model of work-in-process are still challenging because the real-time changes during the machining process are hard to be perceived and simulated. These challenges can be solved through the continuous fusion of manufacturing technologies and new generation information technologies [32]. These days, the focus is given on the realization of DT models on the specific product and machines instead of the whole manufacturing system. Another challenges in the implementation of the DT models include insufficient possibilities for synchronization between the physical and the digital world, the missing of high-fidelity models for simulation and virtual testing in different scales, the difficulties in the prediction of complex systems, as well as the challenges with gathering and processing large data sets [29]. Moreover, challenges related to enormous data collection, model creation, lack of awareness of model and methodology, and resistance companies to change are still unsolved issues in the realization of DT models [23]. More disputes on the applications of DT have been indicated by manufacturers including high cost and data security questions [5]. The data acquisition problem is another challenge in the realization of DT models in small and medium-sized companies to fulfil the real-time requirements for DT application. Moreover, now days missing standardization is a big issue that should be solved to implement DT across companies. Therefore, these problems are believed to be the main reason behind the slow adaptation of DT technology by the companies.

Therefore, still, there is further research that needs to develop standards and improve methods for DT modeling that can be used in real-case applications to extend its role in industrial operations. Moreover, intensive research works are expected on feasible solutions to adapt the DT models in complex manufacturing systems.

6. Conclusion

DT plays a major role in the production, maintenance, and after-sales services. However, during the review, many papers discuss the application of DT models and little is known about the role of DT in the aforementioned domains of industrial operations. In response, this literature review has asked the following question: what is the current state-of-the-art on the role of DT models and challenges in the implementation of the model in production, predictive maintenance and after-sale services in the context of industrial operations? From the systematic review, a special emphasis is devoted to the application of DT models in the production and predictive maintenance, and the remaining papers have described the use of the DT model in the after-sale services. Moreover, the review discusses challenges related to the implementation of DT models to extend their role in industrial operations. This review is essential to give insights for industrial sectors, practitioners and researchers to improve their understanding of the current role of DT models in industrial operations and challenges for real case implementation.

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