Received: 7 May 2020 | Revised: 10 September 2020 | Accepted: 2 October 2020

IET Collaborative Intelligent Manufacturing

DOI: 10.1049/cim2.12010

REVIEW

Digital Twin models in industrial operations: State-of-the-art and future research directions

Tsega Y. Melesse | Valentina Di Pasquale | Stefano Riemma

Department of Industrial Engineering, University of Salerno, Fisciano, Salerno, Italy

Correspondence

Tsega Y. Melesse, Department of Industrial Engineering, University of Salerno, Via G. Paolo II, Fisciano, Salerno, Italy.
Email: tmelesse@unisa.it

Funding information

National Operational Programme Research and Innovation 2014–2020, Grant/Award Number: CUP. D44J18000280006

Abstract

A Digital Twin is a virtual representation of a physical product, asset, process, system, or service that allows us to understand, predict, and optimise their performance for better business outcomes. Recently, the use of Digital Twin in industrial operations has attracted the attention of many scholars and industrial sectors. Despite this, there is still a need to identify its value in industrial operations mainly in production, predictive maintenance, and after-sales services. Similarly, the implementation of a Digital Twin still faces many challenges. In response, a systematic literature review and analysis of 41 papers published between 2016 and 11 July 2020 have been carried out to examine recently published works in the field. Future research directions in the area are also highlighted. The result reveals that, regardless of the challenges, the role of Digital Twin in the advancement of industrial operations, especially production and predictive maintenance is highly significant. However, its role in after-sales services remains limited. Insights are offered for research scholars, companies, and practitioners to understand the current state-of-the-art and challenges, and to indicate future research possibilities in the field.

1 | INTRODUCTION

Digital Twin (DT) is a new concept and technology that evolved with the development of Industry 4.0. It is becoming increasingly important and attracting the attention of many sectors [1,2]. DT is one of the enabling tools of Industry 4.0 that integrates the actual physical system with its virtual replica with the help of models, sensors, data, and software to monitor and analyse future performance. It is the virtual model of a product or asset, connected to the related physical prototype, for instance via the Internet of Things (IoT), that visually enhances data flow, communication, and collaboration across engineering, operations, supply chain, and service. Many definitions have been provided by companies and researchers for DT, however, there is no common definition. Conceptually, it is a living model of the system that can continually be updated with incoming data from the operating environment to monitor the current status and predict the future behaviour of a physical system using data and information (Figure 1). It is considered as a concept model that contains three main parts: physical product in real space, virtual product in virtual space, and data and information connections that tie virtual and real products together.

DT has become one of the hottest topics in manufacturing today because it promises to improve innovation and design, visually enhance collaboration, and enable the ongoing operation of connected products and assets. It provides live, or near real-time, information and insights for manufacturers and asset operators to proactively improve, optimise, and transform businesses using emerging technologies like IoT, Big Data, edge computing, machine learning, and predictive analytics.

It is considered as a non-destructive testing environment developed with the emergence of Industry 4.0 and smart manufacturing [3,4]. The realisation of this technology needs supporting tools including cloud service, simulation, and machine learning algorithms [4–7]. With the help of these enabling tools, it can enhance the transparency of the operating environment, optimisation of multiple characteristics of the system, and the prediction of future performance using real-time data. At its most base level, DT uses three-dimensional (3D) models and simulation software to create a full, living, digital model of a product and its associated manufacturing

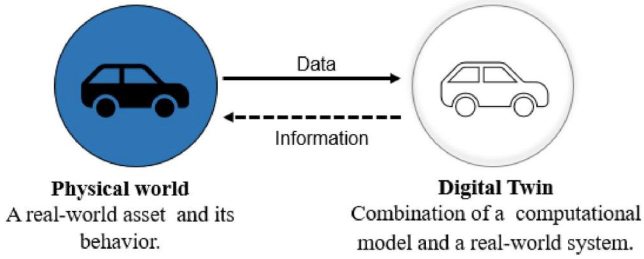

FIGURE 1 Concept of Digital Twin

processes, or assets, and their related environment. Essentially, DTs are the extended application of simulation and visualisation throughout a digitally transformed organisation, for better communication and collaboration.

In practice, DT might not be an accurate copy of the product or asset but is rather an applicable abstraction reflecting valuable data. It should be developed based on being fit for purpose and it is not inevitably a realistic representation of a system or a physical asset. From the perspective of industrial operations, it has the product's information from the beginning to disposal. Thus, it becomes an important part of model-based system engineering to integrate simulation of a system into its corresponding twin. Most significantly, it broadens the concept of model-based system engineering from the engineering and manufacturing phase to operation and service.

Today, modelling and simulation have become standard for engineering support, decision-making process, and evaluation of the impact of production changes by providing fast reacting on time. Hence, using these standards, DT is becoming a vital tool for system development, operation optimisation, and failure prediction. It can help companies in several stages of operation including production, predictive maintenance, and service providing a reduction in both development time and time-to-market, quality improvement, and meeting of customer demands through virtual representations of physical systems.

DT replicates the physical properties of a product or system and enables Multiphysics simulations to deliver predictive engineering insight across the lifecycle of the product. During this case, assets feed messages to the DT and help to resolve possible issues, predict maintenance possibilities, and improve the performance of next-generation products. Therefore, companies can use DT to optimise the designs before costly prototyping and physical testing processes. To meet these objectives and for proper functioning, it must be supported by accurate information about the operations, history, and current state of the system. Thus, based on available information, the user or the autonomous system can make the proper decision about the actual performance and future production performance.

Unlike traditional simulation, DT has the capability to determine the schedule for preventive maintenance, understanding how the physical twin is performing, observing system performance, promoting traceability, facilitating refinement of assumptions, enabling maintainers to troubleshoot, and combining IoT data with the physical system. Therefore, the use of DT can support companies in terms of improving capabilities in production optimisation and predictive maintenance during industrial operations, providing a great business outcome. Moreover, it can enable companies to gain a competitive advantage through adaptation to increased uncertainties, customer demands, and resource costs [3]. As a result, the interest of organisations to adopt and deploy DT has increased rapidly due to its capability to provide relevant and contextual information on business, products, assets, operations, customers, and driving operational efficiency and innovation. Moreover, it can foster new models including customer intimacy, new revenue streams, ecosystem collaboration, and more.

The role of DT in industrial operations, especially in production, predictive maintenance, and after-sale services, is not well defined. Recently, several studies have been conducted on the uses of DT models. Although past research works have covered a wide range of DT applications, the focus here is on the role of DT in three phases of industrial operations analysing the state-of-the-art, common challenges during the implementation of DT, and proposing the future direction of the research work.

Section 2 presents the research method used during the review. Section 3 reports the results from the literature, while Section 4 discusses the role of DT models in three application phases. Section 5 provides information on the challenges during the real-world implementation of DT and possible solutions. Finally, Section 6 provides the conclusions and directions of future work.

2 | METHOD

An extension of work originally presented at an international conference on Industry 4.0 and smart manufacturing is presented [8]. The systematic literature review method followed by [8–11] has been used, with updates and extension provided using recently published papers aiming to show the recent uses of DT models in production, predictive maintenance, and after-sales services. The following questions are answered: What is the current state-of-the-art on the use of DT models in industrial operations mainly in production, predictive maintenance, and after-sale services? What are the common challenges during the implementation? What can be possible solutions? Moreover, future research directions are indicated.

The methodology used to collect and analyse papers is described in Figures 2 and 3. The search of papers was mainly focussed on two databases, Web of Science and Scopus, well organised and top academic databases for literature search and survey. DT is a core, young, and recently growing technology in the realisation of cyber-physical systems in smart manufacturing. Therefore, to analyse the current trend, recent papers published between 2016 and 11 July 2020 have been considered. During the search of papers, key terms of 'digital twin models', 'predictive maintenance', 'production', 'after-sale services', and 'operations' have been used, combined with the Boolean operator 'AND'. In the databases, articles written only in English were considered and analysed after uploading into reference management software (i.e. Mendeley).

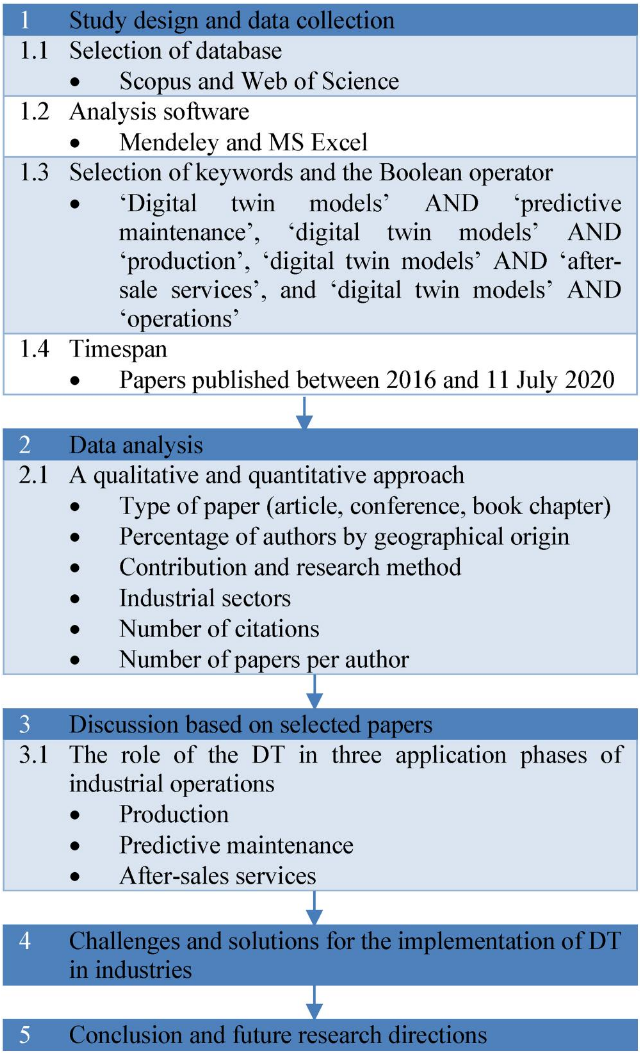

FIGURE 2 Review detail

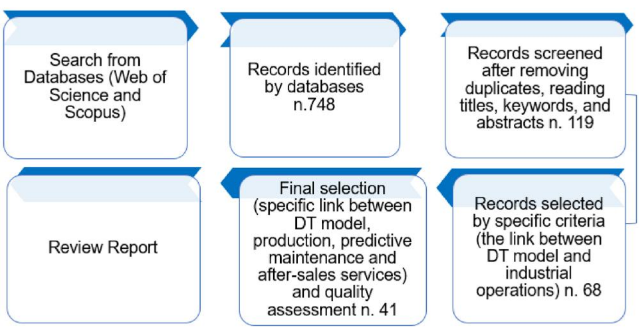

FIGURE 3 Review process

The selection of published papers was done following two different phases. In the first phase, all the papers were checked for relevance and clustered into 'included' and 'excluded' categories using the specific criteria described in Figure 3. The screening criteria were applied based on the availability of full articles, key concepts, and considering the link between DT and the three phases of industrial operations. In the second phase, the assessment of selected papers was done by reading the full text of the articles. All articles were assessed to ensure that they were a fit within the scope of the topic. Thus, articles that made only a minor contribution to the topic area were excluded. Finally, the extracted data was structured and stored in MS Excel to analyse the result.

The characterisation of selected papers was done based on different considerations. The first criterion was focussed on the contribution and research method. Under contribution, papers were classified in terms of objectives (i.e. state-of-the-art, framework development, method development, and others). Similarly, the research methodology papers were arranged into reviews, case studies, experimental, and others. To analyse the impact of selected papers, the top 10 highly cited articles are ranked in Table 1. Finally, the selected papers were characterised in terms of the number of authors per each paper to assess the effect of collaboration on the quality of work (Table 2).

3 | RESULTS

Initially, 748 papers appeared in the search results using a combination of key terms as described in Figure 3. After removing duplicates, reading titles, abstracts, and keywords, 119 articles were screened out for the further review steps. In the next phase of screening, the inclusion of 68 papers was done considering the focus of the entire content on the role of DT in industrial operations. In this stage, the paper quality and the associations between DT modelling and the role in the production, predictive maintenance, and after-sales services were strictly considered and 41 papers were included in the final review and analysis.

According to the analysis of selected papers (Table 3), most of the studies included in the final selection were articles (67%), followed by conference papers (28%) and book chapters (5%).

The use of DT technology is still attracting researchers in different countries. To check the impact of individual countries in the field, the analysis of countries of reference was done based on the affiliation of the authors (Figure 4). Based on this analysis, most of the researchers were from Germany, which is the birthplace of Industry 4.0. Then, China took second position in the research of the focus area followed by France and other European countries, Asian countries, African countries, Canada, and the USA.

The strong dominance of authors from Germany and China is believed to be highly linked with the effectiveness of their proposed national strategies of Industry 4.0 [12] and Made in China 2025 [13], respectively.

According to Table 4, the selected papers were classified based on the publication year, application domains, contribution, and methodology. A rapid increase in the publication rate can be seen for the years 2018 and 2019. The highest research area appears to be production-related and the research in this phase is still increasing. In general, the research trend in the application of DT in three application domains has recently

TABLE 1 Ranking of authors based on citation

Rank	Title	Authors	Number of citations	Journal
1	Digital Twin-driven product design framework	Tao et al.	141	*International Journal of Production Research*
2	Digital Twin service towards smart manufacturing	Qi et al.	72	*Procedia CIRP*
3	Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process	Stief et al.	37	*Procedia CIRP*
4	The role of data fusion in predictive maintenance using Digital Twin	Liu et al.	34	*AIP Conference Proceedings*
5	Digital transformation of manufacturing through cloud services and resource virtualization	Borangiu et al.	30	*Computers in Industry*
6	Smart factories: South Korean and Swedish examples on manufacturing settings	Wiktorsson et al.	21	*Procedia Manufacturing*
7	Design and implementation of a Digital Twin application for a connected micro smart factory	Park et al.	21	*International Journal of Computer Integrated Manufacturing*
8	Modular fault ascription and corrective maintenance using a Digital Twin	Vathoopan et al.	17	*IFAC-PapersOnLine*
9	Knowledge-driven Digital Twin manufacturing cell towards intelligent manufacturing	Zhou et al.	15	*International Journal of Production Research*
10	Machine learning-based Digital Twin framework for production optimization in petrochemical industry	Min et al.	15	*International Journal of Information Management*

TABLE 2 Number of authors per paper

Number of authors	Number of papers	Percentage
2	5	12.2
3	12	29.28
4	8	19.51
5	9	21.95
6	1	2.44
7	2	4.87
8	2	4.87
10	1	2.44

TABLE 3 Editorial classification of selected papers

Document type	Number of papers (%)
Articles	67
Conference paper	28
Book chapters	5

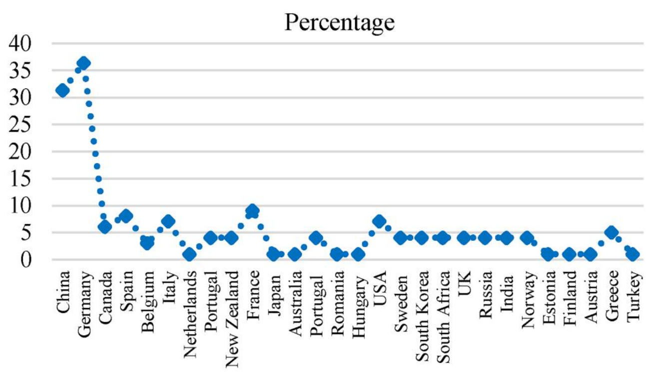

FIGURE 4 Distribution of authors by geographical origin

gained momentum and the interest of researchers has grown rapidly (Figure 5). During this review, the 2020 data is still incomplete and the number of papers this year appears to be lower because the research was carried out focussing on papers that appeared in the search until 11 July 2020.

Most of the selected publications have focussed on the development of the framework and methodology. This contribution mainly comes from review papers which focus on the development of a framework for the application of DT. In comparison with other methods, experimental works remain limited. This could be due to the requirement of advanced technology and the limitations of a knowledge-based approach towards creating DT models.

Nowadays, DT is attracting the attention of different sectors (Table 5). The manufacturing sector has dominated using this technology and the application in the service and other sectors remains low and sectors like agriculture and the food and beverage industry are showing good motivation to use DT.

The ranking of the top 10 authors has been summarised in Table 1 to identify influential researchers in the field. Thus, Tao, Sui, Liu, et al. lead the field with 141 citations followed by Qi, Tao, Zuo, et al. and Stief, Dantan, Etienne, et al. It is evident that the works of these authors have had a momentous impact in three application domains from 2016 to 11 July 2020.

Based on the analysis of 41 selected papers, 51.2% of contributions were derived from a collaboration between three

TABLE 4 Analysis based on the contribution, method, year of publication, and application domain

Classification criteria and domain		Production	Predictive maintenance	After-sales services
Publication year	2020	4	4	1
	2019	13	9	1
	2018	3	3	1
	2017	1	–	–
	2016	1	–	–
Method	Review	8	5	2
	Case study	6	7	1
	Experimental	4	3	–
	Others	4	1	–
Contribution	State-of-the-art	4	3	–
	Method	10	5	1
	Framework	5	5	1
	Others	3	3	1

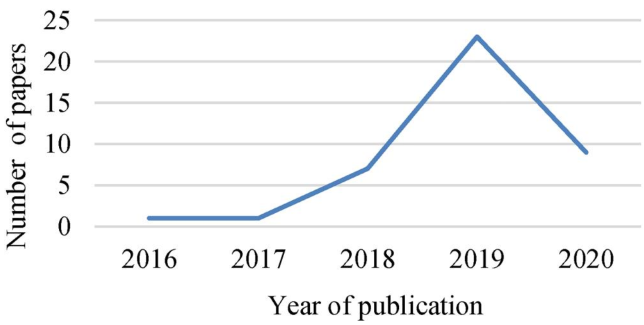

FIGURE 5 Distribution of publications from 2016 to 11 July 2020

TABLE 5 Principal industrial sectors

Sectors	Number of papers	References
Manufacturing	27	[3,14–38]
Services	4	[39–42]
Oil and gas	3	[5,43,44]
Transportation	1	[45]
Food and beverage	1	[46]
Agriculture	1	[47]
Aerospace	2	[4,48]
Construction	1	[49]
Energy	1	[50]

and five authors (Table 2). The highest number of citations was also recorded for those with more than three authors. Although these records sometimes lead to false information because of errors during citation, the result reveals a direct correlation between the impact and an increase in the number of authors.

4 | DISCUSSION

DT is an important tool that can be used in many phases of industrial operation from product design to the disposal stage. Its role has extended to the design, manufacturing, prediction, and monitoring of physical assets in a transparent manner [25,51,52]. Besides, DT can enhance the optimisation, and improve the communication and automation of a system [51]. It can be used in prediction, monitoring, and control of the system for safety reasons, and system diagnosis aimed at the analysis of unpredicted interruptions during the operation [53]. To realise this objective, the operational status of devices and certain components should be captured in real time to reduce disturbances and improve the accuracy of the operation. To date, several companies have already implemented DT to improve their operations and business outcomes, mitigating different challenges (Table 6). Table 7 describes some of the practical examples of DT found in the literature.

The value of DT has highly related to its capability to utilise data generated during different stages of the product life cycle from design to the disposal phase [55] (Figure 6). With this motivation, traditional manufacturing is transforming into smart manufacturing with the help of DT combined with machine learning, the Internet of Things, and data analytics to improve the level of automation and flexibility.

DT can be applied at different levels including component, asset, system, or unit, or as a process twin [56] (Figure 7).

The component twin is a representation of a major part of assets that has a significant impact on the operation of the system and the asset twin focuses on the entire asset. Collecting these assets will create a network of system or unit twins that provides visibility in a set of different types of equipment. Examples of different types of DT and their applications have been summarised (Table 8).

TABLE 6 Use of Digital Twin to mitigate challenges in the companies [54]

Problems	Approach
Complexity	Increasing product, supply chain, and demand complexity mandates manufacturers to manage risk and safety, improve product and asset performance, and maintain high levels of enterprise-wide quality
Ecosystems	Extending and broadening external networks of suppliers and partners, many of whom provide design and operations support
Global and local market	Highly competitive global markets need to be served at a local level with unique requirements and capabilities
Customer experience	Closer collaboration with customers is needed for customised or individualised products across their life span
Data	Massive amounts of structured and unstructured data from IoT, extended supply chains, and multiple disparate manufacturing plants or facilities
Connected, *"always-on"*	Products and assets can be tracked throughout their life cycle, and customers expect high levels of quality and service because of this
Service revenue	Connectivity provides an opportunity for manufacturers to leverage connected asset and product data to ensure high levels of service, value-added services, and an increase in service revenue

TABLE 7 Real-case examples of Digital Twin models

Sector	Purpose	Description
Oil and gas industry	Studying erosion in an electrical submersible pump	DT can be used to monitor and simulate erosion rates to predict the remaining life of the physical pump
Energy	Investigating stress and fatigue in a wind turbine yaw motor	DT enables accurate monitoring of fatigue levels by early detection of faults and improving diagnostic capabilities
Natural gas	Analysing fatigue in a looped pipeline section	Simulation with DT can be used in the prediction of faults that can cause gas leakage in pipeline systems
Road	Extending the lifetime of a bridge	DT provides insights into the material behaviour DT of a bridge to analyse the stress behaviour of the bridge during its lifetime by using sensors attached to the structure

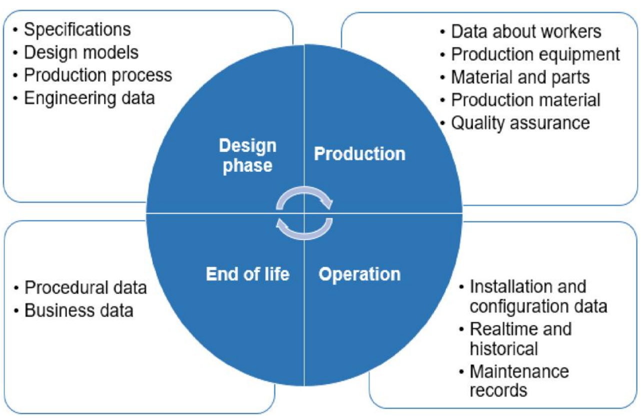

FIGURE 6 Use of Digital Twin in product life cycle management [55]

The section below discusses the roles of DT in selected phases of industrial operations. Commonly mentioned roles of DT in production, predictive maintenance, and after-sales services are summarised in Figure 8.

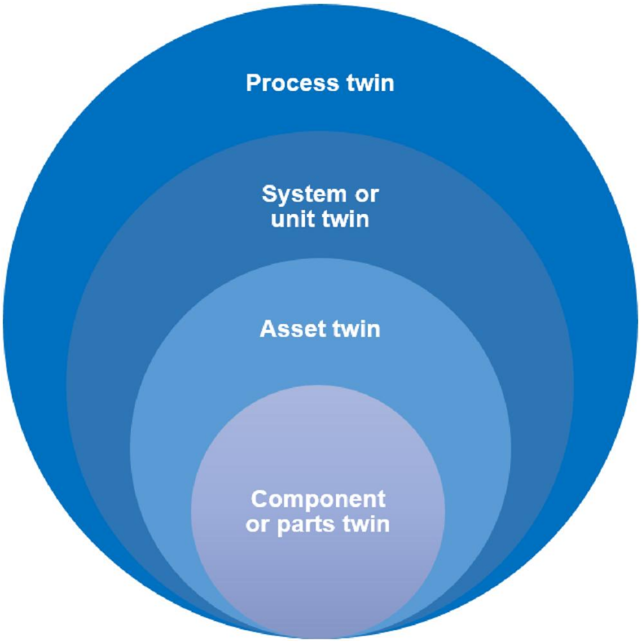

FIGURE 7 Levels of Digital Twin [56]

TABLE 8 Common types of DT and their applications

Type of DT	Application	References
Component	Estimation of grasping point locations on objects	[14]
System/unit	Optical object tracking	[3]
Process	Smart manufacturing	[16]
Process	Augmented reality industrial solutions	[17]
Process	Decision support	[24,29,55]
System	Aircraft predictive maintenance	[4,49]
System	Maintenance	[16,27]
Process	System integration	[57]
System	Smart factory and cyber-physical production systems	[6]
System	Optimisation of plant and machinery	[46,47]
Component	Human–robot collaborative system	[52,58]
System	Micro-manufacturing	[26,59]

4.1 | Utilising Digital Twin in production phases

DT is a virtual model characterised by a continuous update of the actual state using real-time data. This can be helpful to evaluate an operating system under different conditions. Therefore, using what-if analysis, various scenarios of the production system can be improved and optimised. Moreover, visibility and transparency of operations can be enhanced through virtualisation during the production and the behaviour of individual devices can be monitored to integrate the whole system of manufacturing for a better business outcome [28]. DT has also an important role in the development of new value creation using product-as-a-service business models. For instance, one study [37] has described the use of this approach in the shop-floor management system in the Logistics Learning Factory.

Small and medium-sized enterprises can improve the capability of real-time data acquisition systems and operational performance using DT [30,55,60]. DT can enhance a virtual representation and synchronisation of the production system in the operational environment. For example, research [3] has described the application of DT in object tracking using industrial robots. In this case, detected objects have been added to the DT model of the cell along with the robot, creating a synchronised virtual representation of the system. This work has described the transformation of an extended environment into a virtual representation where the sensor captures images and information is extracted using the designed application.

Two studies [30,52] have shown the use of DT in the simulation of the work environment for assembly tasks supporting cooperation between humans and machines. They have also presented the importance of DT in the human–robot production system in the life cycle ranging from design to operation, proposing an implementation framework and using a case study to demonstrate the advantages. Accordingly, the advantages have been described in terms of risks of financial loss and due to human injury in a real-world environment.

DT can improve the ergonomics and safety of the manufacturing system. One study [14] has demonstrated the application of DT in the production system to optimise the safety and ergonomics of the working environment. Similarly, it has the advantage of improving the level of automation, adaptability, and flexibility [35,59,61,62], operational efficiency [63], cost reduction [49], solving problems of regulatory difficulties [50], and the creation of new revenues adding product features and business models [64]. Production optimisation [24] is another key function of DT where many researchers are currently focussing. The use case in petroleum industries [5,44] describes the effectiveness of DT technology to optimise production by using machine learning-based frameworks. Moreover, DT improves the status of companies in digital monitoring and enhancing the function of interconnected devices throughout the production system [6,25,32,33,65]. It can be used as a supporting tool for other industrial operations to reduce complexities in many processes, including order management [55] and horizontal and vertical integration of production systems [65]. These enable companies to meet customer needs and manage their resources properly. Besides, DT improves the safety and reliability of operations through condition monitoring of the production system [45].

4.2 | Supporting predictive maintenance with Digital Twin

These days, industries are shifting from reactive maintenance to predictive and proactive maintenance to improve efficiency, extend the life cycle, and reduce the operational costs of their asset. The capability of DT to predict the future behaviour of an operating system or asset is considered a great input in large industrial sectors. By using real-time data and data-driven analytics, DT can predict the future behaviour and impact of the current operating conditions on the remaining life of an asset [4,31,65,66]. Therefore, identifying potential problems can

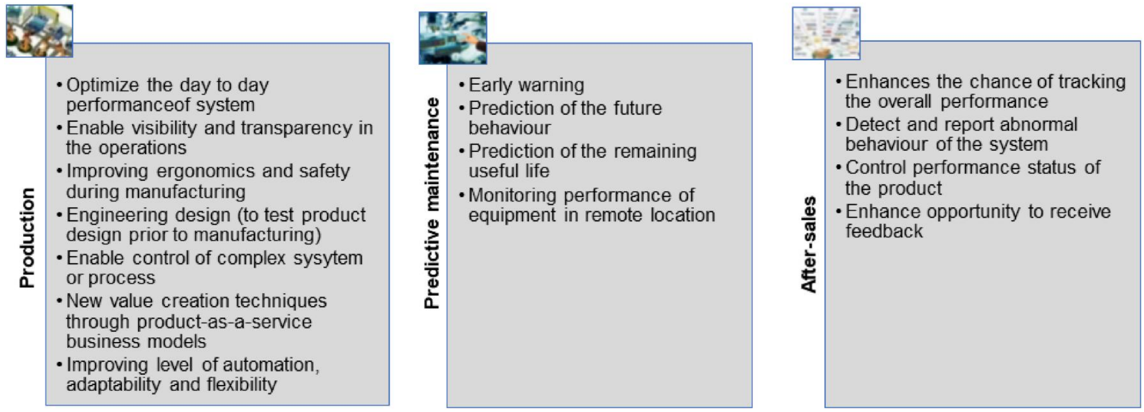

FIGURE 8 Summary of the main roles of Digital Twin in three application phases of industrial operations

enable asset owners to perform predictive maintenance to reduce downtime and operational cost. Thus, DT can deliver accurate forecasting of system failure using incoming data from physical assets [4,7,16,17,36,58,64,67] providing optimisation, early warning, and prediction capabilities. This functionality of DT is expected to have a paramount role in the performance of future industries. For example, the use of DT in the predictive maintenance of aircraft has been described by [4]. This study has applied the use of integrating the simulation and modelling ecosystem to maintain, overhaul, and repair aircraft using IoT and cloud computing systems. The data fusion technique was applied to improve the velocity, variety, and volume of data flow. Similarly, [48] has created a mathematical framework to establish DT for aircraft dynamic systems using sensors, the IoT, and deploying on the cloud computing systems.

4.3 | Using Digital Twin in the after-sales services

According to the study [68], after-sales services can improve profit by 80% in many companies providing competitive advantages. Despite this, the efforts of research into the use of DT in this application phase remain limited.

DT can support companies to monitor their sold items for sudden failure. Therefore, the capability of monitoring the overall performance and maintenance history of products can help manufacturers to gain more trust from their customers, detecting abnormal conditions and providing insights for maintenance. Besides, DT can enable the service sector to achieve the goal of smart manufacturing [16], improving information visibility throughout the life cycle. For instance, two studies [57,69] have shown the application of DT to trace the status of devices. The effectiveness of this traceability and security can be improved with the use of blockchain technology. Adaptation of this technology is considered as a key solution to monitor a physical object from production to after-sales. With the help of DT, companies can also improve the interaction with their customers to provide support and receive feedback about their services. Ultimately, they can improve brand loyalty by adapting to the needs of customers. One study [47] has shown how manufacturers were able to optimise the operation of smart farming of potato harvesting using feedback from customers.

5 | CHALLENGES IN THE IMPLEMENTATION OF DIGITAL TWIN

Implementation of DT still faces challenges including lack of detailed methodology and standards, difficulties in collecting and storing large amounts of data [44,70,71], developing data acquisition system, synchronisation problems, modelling of a complex system, lack of awareness, resistance of companies to adopting the technology [59], and difficulties in constructing, understanding, controlling, and simulating real-time changes in the system.

High-fidelity models are required to simulate and test the product or process in a virtual environment by reducing development time and cost [26,72] The issue of high investment cost and data security is still a hindrance to many companies making DT part of their daily life [55]. There are also problems related to the lack of suitable business models and the use of digital services and goods is still new and implementation is difficult for many manufacturers [47].

A study [73] has identified challenges such as engineering, technology, commercial, data, and others (Figure 9). Engineering challenges arise from the complexity of the system to make system predictions and lack of standards to ensure efficient communication, human and product safety, the security of the data, and structural integrity. Technological development is also a factor that is hindering the implementation of DT technology. This can be evaluated in terms of cost and time. Therefore, the highest cost of IT facilities, and the long time requirements to develop adequate technologies are among critical challenges. Removing cultural barriers, the mindset towards data sharing, and investments to improve software and services can be solutions to these challenges. The commercial challenge includes scalability [41] issues due to the architecture, the capability to

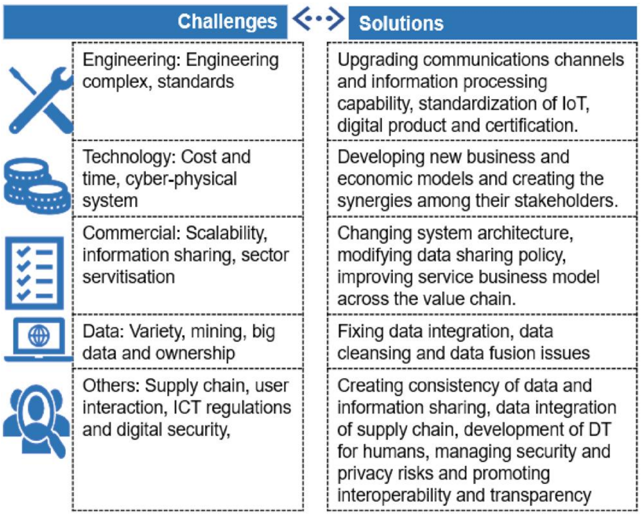

FIGURE 9 Challenges and solutions for the application of Digital Twin

change the level of parameters, the complexity of the supply chain, and computational power. Also, information sharing is considered the biggest obstacle created by the complex policies of companies regarding the ownership of data.

The technological challenge is related to the servitisation issue because service delivery remains difficult and is dependent on the company's business model, and management of customer and risk management. Therefore, end-to-end integration should be developed throughout communication to solve the issue of privacy risk and improve transparency in data flow during DT usage.

Cybersecurity is another challenge to DT use and there are several pillars including security, data encryption, security audit, monitoring live events, and responding to incidents, identity, and management of devices [44,74]. To ensure data security, DT should be supported by a security audit for the visibility of the transaction and to identify the devices and users. Moreover, it is mandatory to ensure the right level of access to the activities they have performed. Similarly, data encryption can be used as a solution to protect the injection of false data by malicious actors and it should be enabled by the capability of live event monitoring and responses to detect abnormal behaviour during the operations. Thus, DT developers should be able to authenticate and identify users to monitor who is attempting to access and send data to the data set or system.

6 | CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The roles of DT in three phases of industrial operations have been presented, exploring the current trend of research in the area, and identifying the challenges for its implementation by using a systematic literature review. Therefore, one of the main contributions has been analysing recently published works and understanding the state-of-the-art on the uses of DT in production, predictive maintenance, and after-sales services.

A discussion of these application phases has been provided in detail. In particular, the discussion has focussed on the use of DT to support the three phases of industrial operations in their day-to-day performance to deliver business outcomes. Another contribution relies on providing a solution to the challenges of implementing DT models at the industrial level.

There are several gaps regarding the use of DT in three phases of industrial operation that could benefit further research in the field:

- More methods should be developed to implement DT, based on current knowledge.
- Benchmark studies between models developed in the same sector are needed to compare and identify best practices.
- The focus on the after-sales field remains limited and more research is needed to support this operational phase. There is, therefore, a call for more research on the use of DT technology in the area of after-sales services.
- According to the literature analysis, the potential use of DT in the support of the supply chain sector has not been well studied. Therefore, future work is planned on the development of the methodology and implementation of DT in this area, with special emphasis on the food supply chain.

ACKNOWLEDGEMENT

This work was supported by National Operational Programme Research and Innovation 2014–2020 (CUP. D44J18000280006).

REFERENCES

1. Liao, Y., et al.: Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. Int J Prod Res. 55, 3609–3629 (2017)
2. Xu, L Da., Xu, EL., Li, L.: Industry 4.0: state of the art and future trends. Int J Prod Res. 56, 2941–2962 (2018)
3. Tammaro, A., et al.: Extending industrial digital twins with optical object tracking. Eurographics Symp Geom Process. 36, 23–26 (2017)
4. Liu, Z., Meyendorf, N., Mrad, N.: The role of data fusion in predictive maintenance using digital twin. AIP Conf Proc. (2018)
5. Min, Q., et al.: Machine learning based digital twin framework for production optimization in Petrochemical industry. Int J Inf Manage, 1–18 (2019)
6. Liu, C., et al.: A cyber-physical machine tools Platform using OPC UA and MTConnect. J Manuf Syst. 51, 61–74 (2019)
7. Diez-Olivan, A., et al.: Data fusion and machine learning for industrial prognosis: trends and perspectives towards Industry 4.0. Inf Fusion. 50, 92–111 (2019)
8. Melesse, TY., Di Pasquale, V., Riemma, S.: Digital twin models in industrial operations: a systematic literature review. Procedia Manuf. 42, 267–272 (2020)
9. Di Pasquale, V., et al.: Human reliability in manual assembly systems: a Systematic Literature Review. IFAC-PapersOnLine. 51, 675–680 (2018)
10. Di Pasquale, V., et al.: Human error in industrial maintenance: a systematic literature review. Proc Summer Sch Fr Turco (2017)
11. Seuring, S., Müller, M.: From a literature review to a conceptual framework for sustainable supply chain management. J Clean Prod. 16, 1699–1710 (2008)
12. Erol, S., Schumacher, A., Sihn, W.: 'Strategic guidance towards Industry 4.0 – a three-stage process model', pp. 495–501. Coma (2016)
13. Huimin, M., et al.: 'Strategic plan of 'Made in China 2025' and its implementation'. Anal Impacts Ind 40 Mod Bus Environ., 1–23 (2018)

14. Arisoy, E.B., et al.: A data-driven approach to predict Hand positions for two-hand grasps of industrial objects. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 50077, p. V01AT02A067). American Society of Mechanical Engineers (2016)
15. Zutshi, A., Grilo, A.: Developing a digital Platform architecture and analysing its impact on industrial engineering. Comput Ind Eng (2019)
16. Tao, F., Zhang, M., Nee, AYC: Digital twin driven smart Manufacturing, 1st ed, pp. 3–28.Academic press (2019)
17. Kholopov, VA., Antonov, S V., Kashirskaya, EN: Application of the digital twin concept to solve the monitoring task of machine-Building technological process. Proc - 2019 Int Russ Autom Conf RusAutoCon 2019, 8–12 (2019)
18. Park, KT., et al.: Design and implementation of a digital twin application for a connected micro smart factory. Int J Comput Integr Manuf. 32, 596–614 (2019)
19. Aivaliotis, P., Georgoulias, K., Chryssolouris, G.: The use of Digital Twin for predictive maintenance in manufacturing. Int J Comput Integr Manuf. 32, 1067–1080 (2019)
20. Janda, P., Hajicek, Z, Bernardin, P.: Implementation of the digital twin methodology. Ann DAAAM Proc Int DAAAM Symp. 30, 533–538 (2019)
21. Lin, WD., Low, MYH: Concept and implementation of a cyber-physical digital twin for a SMT line. IEEE Int Conf Ind Eng Eng Manag, 1455–1459 (2019)
22. Gao, Y., et al.: Real-time modelling and simulation method of digital twin production line. In: Proc 2019 IEEE 8th Jt Int Inf Technol Artif Intell Conf ITAIC 2019, pp. 1639–1642 (2019)
23. Werner, A., Zimmermann, N., Lentes, J.: Approach for a holistic predictive maintenance strategy by incorporating a digital twin. Procedia Manuf. 39, 1743–1751 (2019)
24. Wiktorsson, M., et al.: Smart Factories: South Korean and Swedish examples on manufacturing settings. Procedia Manuf. 25, 471–478 (2018)
25. Fera, M., et al.: Towards digital twin implementation for assessing production line performance and Balancing. Sensors, 97 (2020)
26. Aivaliotis, P., Georgoulias, K., Alexopoulos, K.: Using digital twin for maintenance applications in manufacturing: state of the Art and Gap analysis. In: Proc - 2019 IEEE Int Conf Eng Technol Innov ICE/ITMC 2019 (2019)
27. Chen, Y., et al.: Research on application of digital twin in simulation of Equipment maintenance support. IOP Conf Ser Mater Sci Eng. 782 (2020).032088
28. He, B., Bai, KJ: Digital twin-based sustainable intelligent manufacturing: a review. Adv Manuf (2020)
29. D'Amico, D., et al.: Conceptual framework of a digital twin to evaluate the degradation status of complex engineering systems. Procedia CIRP. 86, 61–67 (2020)
30. Sun, X., et al.: A digital twin-driven approach for the assembly-commissioning of high precision products. Robot Comput Integr Manuf. 61 (2020).101839
31. Tao, F., et al.: Digital twin-driven product design framework. Int J Prod Res. 7543, 1–19 (2019)
32. Vathoopan, M., et al.: Modular fault Ascription and Corrective maintenance using a digital twin. IFAC-PapersOnLine. 51, 1041–1046 (2018)
33. Stief, P., et al.: Integrating the Digital Twin the manufacturing system Design of France into a decision support system for improving the order management process A new methodology to analyse the functional and physical architecture of existing. Procedia CIRP. 72, 225–231 (2018)
34. Rabah, S., et al.: Towards improving the future of manufacturing through digital twin and augmented reality technologies. Procedia Manuf. 17, 460–467 (2018)
35. Qi, Q., et al.: Digital twin service towards smart manufacturing. Procedia CIRP. 72, 237–242 (2018)
36. Zhou, G., et al.: Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing. Int J Prod Res, 1–18 (2019)
37. Qiao, Q., et al.: Digital twin for machining tool condition prediction. Procedia CIRP. 81, 1388–1393 (2019)
38. Borangiu, T., et al.: Digital transformation of manufacturing through cloud services and resource virtualisation. Comput Ind. 108, 150–162 (2019)
39. Papazoglou, MP., Elgammal, A., Krämer, BJ.: Collaborative on-demand product-service systems customisation lifecycle. CIRP J Manuf Sci Technol. (2018)
40. Sun, J., Zhang H., Ma L., et al.: Digital twin in services and industrial product-service systems: review and analysis. Procedia CIRP. 83, 57–60
41. Altun, C., Tavli, B.: 'Social internet of digital twins via Distributed Ledger technologies: application of predictive maintenance'. 27th Telecommun Forum, TELFOR 2019 (2019)
42. Rosen, R., Fischer, J., Boschert, S.: Next generation digital twin: an ecosystem for mechatronic systems. IFAC-PapersOnLine. 52, 265–270 (2019)
43. Bevilacqua, M., et al.: 'Digital twin reference model development to prevent operators' risk in process Plants'. Sustainability, 1088 (2020)
44. Wanasinghe, TR., et al.: Digital twin for the Oil and Gas industry: Overview, research trends, Opportunities, and challenges. IEEE Access. 8, 104175–104197 (2020)
45. Moi, T., Cibicik, A., Rølvåg, T.: Digital twin based condition monitoring of a knuckle boom crane: an experimental study. Eng Fail Anal. 112 (2020). 104517
46. Gericke, GA., et al.: Design of digital twins for optimization of a Water Bottling plant. IECON Proc (Industrial Electron Conf 2019), 5204–5210 (2019)
47. Kampker, A., et al.: Business models for industrial smart services - the example of a digital twin for a product-service-system for potato harvesting. Procedia CIRP. 83, 534–540 (2019)
48. Ganguli, R., Adhikari, S.: The digital twin of discrete dynamic systems: Initial approaches and future challenges. Appl Math Model. 77, 1110–1128 (2020)
49. Khajavi, SH., et al.: Digital Twin: Vision, benefits, boundaries, and creation for buildings. IEEE Access. 7, 147406–147419 (2019)
50. Hu, C., Shi, W., Jiang, L.: Application case of digital twin technology in electric power system. IOP Conf Ser Mater Sci Eng (2020)
51. Tao, F., et al.: Data-driven smart manufacturing. J Manuf Syst. 48, 157–169 (2018)
52. Malik, AA., Bilberg, A.: Digital twins of human-robot collaboration in a production setting. Procedia Manuf. 17, 278–285 (2018)
53. Kritzinger, W., et al.: Digital Twin in manufacturing: a categorical literature review and classification. IFAC-PapersOnLine. 51, 1016–1022 (2018)
54. Digital Twin Concept in Manufacturing Industry. https://jam4.sapjam.com/discussions/M0yqbDBo2Vjs8W026kwwV2. Accessed 01 September 2020
55. Kunath, M., Winkler, H.: Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process. Procedia CIRP. 72, 225–231 (2018)
56. Luigi, M., Roberto, G., Ramin M.: Digital twin. https://www.eng.it/en/white-papers/digital-twin. Accessed 12 August 2019.
57. Heber, D., Groll, M.: Towards a digital twin: how the blockchain can foster E/E-traceability in consideration of model-based systems engineering. Proc Int Conf Eng Des ICED. 3, 321–330 (2017)
58. Aivaliotis, P., et al.: Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance. Procedia CIRP. 81, 417–422 (2019)
59. Lohtander, M., et al.: Micro manufacturing Unit - creating digital twin objects with common engineering software. Procedia Manuf. 17, 468–475 (2018)
60. Uhlemann, THJ., et al.: The digital twin: Demonstrating the potential of real-time data acquisition in production systems. Procedia Manuf. 9, 113–120 (2017)
61. Tolio, T., et al.: Design, management and control of demanufacturing and remanufacturing systems. CIRP Ann - Manuf Technol. 66, 585–609 (2017)
62. Barthelmey, A., et al.: Dynamic digital twin for predictive maintenance in flexible production systems. IECON Proc (Industrial Electron Conf 2019), 4209–4214 (2019)

63. Szpytko, J., Duarte, YS: Digital twins model for Cranes operating in container Terminal. IFAC-PapersOnLine. 52, 25–30 (2019)
64. Etienne, A.: Realizing availability-oriented business models in the capital goods: a new methodology to analyse the functional and physical architecture of industry existing products for an assembly product family identification. Procedia CIRP. 73, 297–303 (2018)
65. Stark, R., Fresemann, C., Lindow, K.: Development and operation of Digital Twins for technical systems and services. 68, 129–132. CIRP Annals (2019). Epub ahead of print
66. Brenner, B., Hummel, V.: Digital twin as enabler for an innovative digital Shopfloor management system in the ESB Logistics learning factory at Reutlingen - University. Procedia Manuf. 9, 198–205 (2017)
67. Rajesh, PK., et al.: Digital twin of an Automotive Brake Pad for predictive maintenance'. Procedia Comput Sci. 165, 18–24 (2019)
68. Dombrowski, U., Malorny, C.: Service planning as a support process for a lean after sales service. Procedia CIRP. 64, 324–329 (2017)
69. Hasan, HR., et al.: A blockchain-based approach for the creation of digital twins. IEEE Access. 8, 34113–34126 (2020)
70. Schleich, B., et al.: Shaping the digital twin for design and production engineering. CIRP Ann - Manuf Technol. 66, 141–144 (2017)
71. Rasheed, A., San, O., Kvamsdal, T.: Digital twin: Values, challenges, and enablers from a modelling perspective. IEEE Access. 8, 21980–22012 (2020)
72. Huang, H., et al.: Towards large-scale simulation of residual stress and distortion in wire and arc additive manufacturing. Addit Manuf. 34 (2020). 101248
73. Singh, S., et al.: Challenges of digital twin in high value manufacturing. SAE Tech Pap. (2018)
74. Gerber, D., Nguyen, B., Gaetani, I.: Digital twin: towards a meaningful framework (2019) https://www.arup.com/perspectives/publications/research/section/digital-twin-towards-a-meaningful-framework

How to cite this article: Melesse TY, Di Pasquale V, Riemma S. Digital Twin models in industrial operations: State-of-the-art and future research directions. *IET Collab. Intell. Manuf.* 2021;3:37–47. https://doi.org/10.1049/cim2.12010