International Journal of Computer Integrated Manufacturing

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tcim20

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To cite this article: Igiri Onaji, Divya Tiwari, Payam Soulatiantork, Boyang Song & Ashutosh Tiwari (2022) Digital twin in manufacturing: conceptual framework and case studies, International Journal of Computer Integrated Manufacturing, 35:8, 831-858, DOI: 10.1080/0951192X.2022.2027014

To link to this article: https://doi.org/10.1080/0951192X.2022.2027014

Published online: 24 Jan 2022.

INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING
2022, VOL. 35, NO. 8, 831–858
https://doi.org/10.1080/0951192X.2022.2027014

Digital twin in manufacturing: conceptual framework and case studies

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ABSTRACT
The digital twin (DT) concept has a key role in the future of the smart manufacturing industry. This review paper aims to investigate the development of the digital twin concept, its maturity and its vital role in the fourth industrial revolution. Having identified its potential functionalities for the digitalisation of the manufacturing industry, the digital twin concept, its origin and perspectives from both the academic and industrial sectors are presented. The identified research gaps, trends and technical limitations hampering the implementation of digital twins are also discussed. In particular, this review attempts to address the research question on *how the digital twin concept can support the realisation of an integrated, flexible and collaborative manufacturing environment which is one of the goals projected by the fourth industrial revolution*. To address this, a conceptual framework supporting an integrated product-process digital twin for application in digitised manufacturing is proposed. The application and benefits of the proposed framework are presented in three case studies.

ARTICLE HISTORY
Received 11 June 2020
Accepted 5 January 2022

KEYWORDS
Digital twin; automation and control; smart manufacturing; Industry 4.0; cyber-physical production systems; product lifecycle management

1. Introduction

1.1. Background

In recent years, the tremendous growth and innovative breakthroughs in the digital world and the increasing integration of information and communication technologies (ICT) with industrial operational technologies (OT) has greatly influenced and redefined the manufacturing industry. This has enabled better energy and resource utilisation, shortened time-to-market for products and enhanced manufacturing flexibility (Rosen et al. 2015; Zhang et al. 2019a). Innovations like the interconnections of intelligent components within factory floors, Internet of Things (IoT), sensor data fusion and cloud computing (CC) technologies has given birth to a new era of manufacturing most often called smart manufacturing/digitised manufacturing (Tao and Zhang 2017; Yun, Park, and Kim 2017). Several national strategies have been developed to harness the potentials of these emerging technologies/innovations within the manufacturing industries. Examples include Industry 4.0 (I4.0) by Germany, Made in China 2025, Strategy 5.0 by Japan, Advanced manufacturing partnership and Industrial internet strategies in the United States of America (USA) (Zhang et al. 2019a).

In manufacturing, the convergence of the virtual space with the physical operational space, to enable the interconnection of virtual elements with their operational physical counterparts (cyber-physical integration) has been a significant challenge for achieving the objectives of smart production (Tao and Zhang 2017; Cheng et al. 2018). The concept of the digital twin (DT) has been discussed for over a decade as an approach to tackle this problem and in recent has gained much more attention worldwide (Cheng et al. 2018; Zhou et al. 2019). This provides the linkage needed to bridge the gap between the physical and virtual space in real-time, interconnect silos of data within a business chain and reinvent the paradigm of demand and supply (Rosen et al. 2015; Schuh and Blum 2016; Yun, Park, and Kim 2017).

1.2. Problem domain

1.2.1. Discussion of the problem

Industry 4.0 drives the manufacturing industry into a new era of autonomous and intelligent information exchange, machine control and interoperable production systems. One of the key goals of Industry 4.0 is connectivity and integration of elements within the production environment (DIN & DKE 2018). This will allow companies to build a data footprint through sensors and

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monitoring of machines/equipment. However, there are challenges associated with the existing structure of manufacturing systems: centralised control structures and heterogeneity of data due to the variability of manufacturing vendor products (Tao et al. 2019). The digital twin concept is presented as a prospective solution to this challenge. This brings us to the research question: *'How does the digital twin concept support the realisation of an integrated, flexible and collaborative manufacturing environment as one of the goals projected by the fourth industrial revolution?'*. By enabling the integration of both physical and virtual spaces, a digital twin of a manufacturing system can provide the integrated platform necessary to harness the potential of generated data. This would see more data-based corrective actions taken in real-time to optimise production lines and increase productivity.

1.2.2. Past work on review

Negri, Fumagalli, and Macchi (2017) reviewed the roles of the digital twin in the cyber-physical system (CPS)-based production systems. This paper also presented the history of the concept, the definitions of the digital twin in scientific literature, its role within Industry 4.0 and some recommendations for future research. Kritzinger et al. (2018) presented a systematic literature review that focussed on the use of digital twin in manufacturing. In the context of production science, they gave a holistic overview highlighting the manufacturing areas in which digital twin has been applied, the concepts, enabling technologies and level of integration in recorded use cases. Having criticised the synonymous use of the terms digital model (DM), digital shadow (DS) and digital twin (DT), they presented these three terms as subcategories of the digital twin based on the level of physical-virtual data integration. Enders and Hoßbach (2019) presented a systematic review providing a comprehensive cross-industry overview of the digital twin applications. Zhang et al. (2019c) published a systematic review that focused on the current state-of-the-art of digital twinning within the context of product-service systems. It was observed that little work had been done in the context of product-service systems area. Only two studies out of the 59 papers focused on product-service systems. In an attempt to build an understanding of the development and applications of the digital twin in industry, Tao et al. (2019) presented a review on digital twin in industry. The focus was on the key component of digital twins, current developments, major digital twin applications, current challenges and lastly, recommendations on possible directions for future work. Aivaliotis, Georgoulias, and Alexopoulos (2019) reviewed the use of the digital twin in the field of maintenance and health prediction. They investigated already existing implementations and proposed ways to improve them. Lu et al. (2020) reviewed digital twin driven smart manufacturing. In the context of industry 4.0, the development of digital twin technologies, impact, reference model, application scenarios and research issues of digital twin towards smart manufacturing were discussed. Jones et al. (2020) presented a systematic literature review with a thematic analysis on 92 digital twin publications from the last 10 years. In characterising the digital twin concept, 13 characteristics were presented, namely, physical entity/twin; virtual entity/twin; physical environment; virtual environment; state; realisation; metrology; twinning; twinning rate; physical-to-virtual connection/twinning; virtual-to-physical connection/twinning; physical processes; and virtual processes.

From the reviews mentioned above, it was observed that there has been an increasing interest in the digital twin concept. However, a variation in the definition, description, classification and application of the concept was observed. Despite the disparity in the perception of the digital twin concept by various interest groups, the last two years have witnessed many use cases in manufacturing (Figure 2) (Tao, Zhang, and Nee 2019). This work creates a holistic picture of the research progress made so far within this field and identified the following focus areas for future research:

(1) Common grounds for varying ideologies to add clarity to their applicability
(2) Tracking of the evolution of the concept up to the current understanding and applications within the manufacturing sector
(3) Integrate both product and process digital twins to utilize their dependencies in a cyber-physical production system (CPPS)
(4) Forging a research roadmap towards achieving the full dividends of the concept within the manufacturing industry

1.3. Novelty and contribution to knowledge

Past reviews have pointed out challenges and research foci within this field (subsection 1.2.2) suggesting that there is a need to track the developments made in tackling these challenges and find possible applications of these solutions within the manufacturing field. This paper makes its contribution by carrying out a thorough literature review to investigate the potentiality of the digital twin concept as an integrated platform to promote flexibility and integration in manufacturing. A flexibility that allows systems to easily adapt to changes in product type, quality, quantity and the integration of the automation information system to support data-driven control methods. In this regard, it has created a holistic picture of the research progress made so far within this field. This includes tracing the evolution and application of the digital twin concept from inception till date, identification of research gaps, trends and technological triggers. This work proposed a digital twin framework as a concept that can integrate both product and process digital twins. This product-process digital twin integration provides the platform for increased flexibility, control and management of the production system for easy adaptation to changes in product type/quality during production. Three case studies have been included, of which two case studies are based on the proposed framework. Finally, limitations in the application of the digital twin concept are presented along with proposed solutions.

In this regard, the rest of the paper is structured as follows: section two presents the research methodology. Section three presents the discussion on the digital twin concept and its application. Section four presents a digital twin framework for smart manufacturing. Section five presents three case studies. Section six discusses identified technical limitations and proposed solutions. Finally, the study concludes with some recommendations for further research.

2. Methodology

This chapter presents the methodology used in the systematic literature review and presents the main quantitative findings. Figure 1 shows the methodology

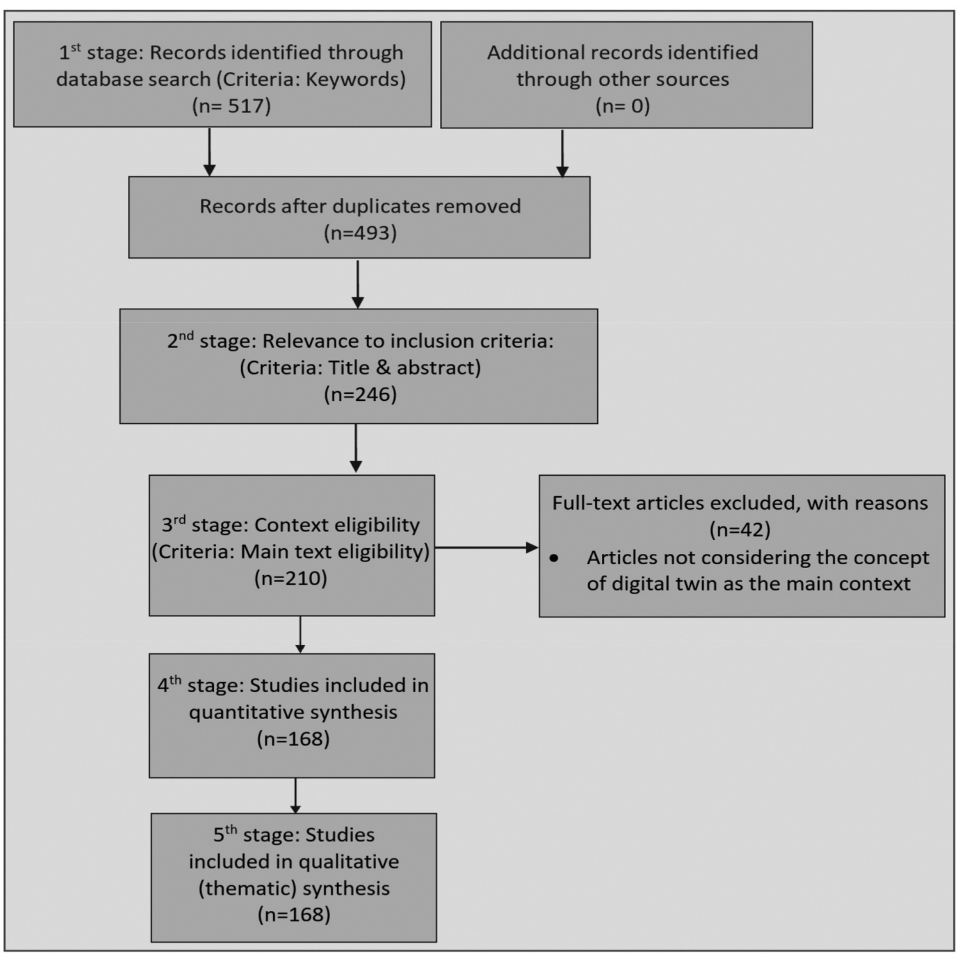


Figure 1. Flow chart of the selection process. Adapted from (Moher et al. 2009)

used to gather the digital twin-related literature. This method involved a literature search of the Scopus and ScienceDirect databases, quantitative and qualitative analyses of the selected papers. The keywords 'digital twin' and 'manufacturing' with the keyword Boolean 'AND' was used for the search. The identification and collation of the critical studies were done using the steps explained in Figure 1: A total of 168 publications were considered for meta-analysis. Unpublished data were not considered.

A meta-analysis was done to increase the power and precision of this research outcome and more importantly using statistical measures, a survey of the landscape enabled the proposition of a map out for future research directions (Stapic et al. 2012). This research may be biased since the choice of which journal article should be included or not was subjective to the researchers' judgment. The definition of quality is dependent on the researchers as such the quality of the articles used in the study may vary with persons. Figure 2(a) presents the number of publications considered in the highlighted years.

Figure 2 demonstrates the growing research interest in the area of the digital twin, especially from the year 2017. Figure 2(b&c) shows an increased application of the concept at a systems and system-of-systems (SoS) levels. These findings reveal a growing acceptance of the concept as an essential driving force/element for the fourth manufacturing generation.

3. Digital twin

This section presents the key findings from the results of the literature review conducted by the authors. This includes the evolution, perspectives and current understanding of the digital twin concept; proposed digital twin frameworks within manufacturing and other technologies used to achieve cyber-physical integration. It also addresses how the digital twin concept supports integration, flexibility and collaboration within the manufacturing environment and lastly, presents a summary of the main outcomes of the literature review.

3.1. *The concept of the digital twin*

The digital twin (Figure 3) is a virtual replica of its physical asset built mainly of structural and behavioural models mainly for basic control, monitoring and evaluation of its performance (Cai et al. 2017; Martinez et al. 2018).

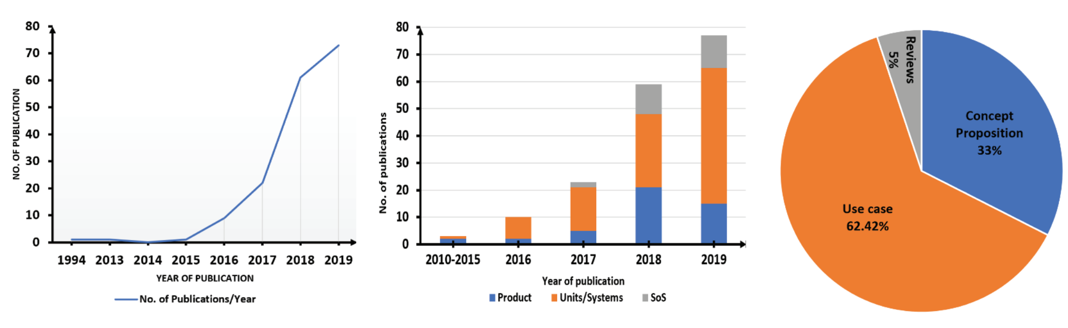
3.1.1. *Characteristics of the digital twin*

A digital twin, as shown in Figure 3 & Figure 8 , has the following characteristics that differentiate it from simulation models (Modoni, Sacco, and Ter kaj 2016; Cheng et al. 2018; Martinez et al. 2018)

(I) Real-time reflection: highly synchronised with the physical space, the virtual space is a real-time reflection of the physical space with a multi-level of fidelity.

(II) Interaction and convergence: This characteristic is further divided as follows

a. Interaction and convergence in physical space: It is a complete integration of system phases, elements, services and interaction. Data generated in various phases of physical space are connected and accessible.



(a) Depicts trend of digital twin research interest (b) Digital twin types (c) Research focus between 1994 to 2019

Figure 2. (a) Depicts trend of digital twin research interest. (b) Digital twin types. (c) Research focus between 1994 to 2019.

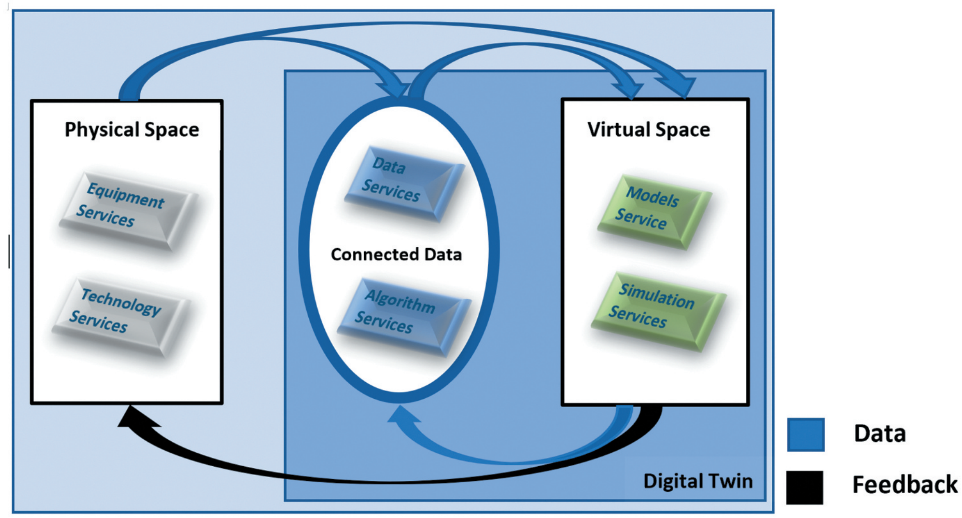


Figure 3. General digital twin architecture.

b. Interaction and convergence between historical data and real-time data: Having both multi-physics models and data-driven approaches, a comprehensive digital twin contains both domain knowledge and timely operational information of the system.

c. Interaction and convergence between the physical and virtual spaces: The digital twin is an integrated platform providing a smooth bidirectional connection between the two spaces.

(III) Self-evolution: The digital twin able to update its data in real-time automatically, mirrors its physical twin. Parallel connectivity allows comparison between the two spaces enabling continuous improvement of the virtual models.

3.2. The evolution of the digital twin concept

Since the public presentation of the digital twin concept, authors have argued on the vision of the digital twin resulting in different definitions and applications (Table 1). In recent years, more authors are inclined to the notion that the vision refers to a comprehensive virtual representation with connectivity to the physical and functional description of the product/system throughout the lifecycle phases (Yun, Park, and Kim 2017; Cheng et al. 2018; Kritzinger et al. 2018). Table 1 presents some identified definitions of the digital twin. It reflects a gradual transformation of the concept and its applicability.

The definitions of the digital twin given by NASA and Grieves reflect a broader view of its existing applications (Shafto et al. 2012; Grieves and Vickers 2016). This research sees the digital twin for manufacturing as a set of integrated virtual information construct of a potential or actual physical system detailed with all necessary minuscule and macro-level of multi-physics, multi-scale geometric and simulative probabilistic specifics, suitable for its creation. Virtual models of suitable granularity with defined functionalities are developed and integrated into a networked system (Cheng et al. 2018). The physical system interlinked with this integrated virtual entity updates it with operational data, thus becoming an exact digital representation of its physical twin (Haag and Anderl 2018). The development of the digital twin for a new physical asset should begin at the design/engineering stage and evolve through the assets' lifecycle (Rosen et al. 2015; Martinez et al. 2018; Qi et al. 2018). For already existing systems, the digital twin can become an additional component modelled to reflect the existing functionalities of the system (Enders and Hoßbach 2019).

3.3. Perspectives on the digital twin

The digital twin concept in an earlier time was applied to product design (Zhang et al. 2019b). In recent times it is perceived to encompass the entire business value chain resulting in digital twins of products, production process, system performance and services (Leng et al. 2019). Despite non-unification in definition and description (Table 1), there is a similarity in the key

Table 1. Identified definitions of the digital twin in literature.

No	Ref	Year	Definition of digital twin
1	(Shafto et al. 2012)	2010–2015	"A Digital twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin".
2	(Zhang et al. 2019a)	2016	"The digital twin is a virtual representation of the real product. It has the product's information since the beginning of the product's life until the disposal of the product".
3	(Grieves and Vickers 2016)	2017	"A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level".
4	(Brenner and Hummel 2017)	2017	"A digital copy of a real factory, machine, worker, etc., that is created and can be independently expanded, automatically updated as well as being globally available in real-time".
5	(Stark, Kind, and Neumeyer 2017)	2017	"A Digital twin is the digital representation of a unique asset (product, machine, service, product service system or another intangible asset), that compromises its properties, condition and behaviour using models, information and data".
6	(Weber et al., 2017)	2017	"A digital representation of all the states and functions of a physical asset".
7	(Blum and Schuh 2017)	2017	"A virtual representation of a product on the shop-floor".
8	(Bohlin et al. 2017)	2017	"A comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in the current and subsequent lifecycle phases".
9	(Negri, Fumagalli, and Macchi 2017)	2017	"The virtual and computerized counterpart of a physical system that can be used to simulate it for various purposes, exploiting a real-time synchronization of the sensed data coming from the field".
10	(Tao et al. 2018)	2018	"A real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them".
11	(Scaglioni and Ferretti 2018)	2018	"A near-real-time digital image of a physical object or process that helps optimize business performance".
12	(Talkhestani et al. 2018)	2018	"A current, digital model of a product or production system that contains a comprehensive physical and functional description of a component or system throughout the lifecycle".
13	(Haag and Anderl 2018)	2018	"A comprehensive digital representation of an individual product. It includes the properties, condition and behaviour of the real-life object through models and data".
14	(Liu, Meyendorf, and Mrad 2018)	2018	"An integrated multi-physics, multiscale, probabilistic simulation of an as-built system enabled by digital threads, that uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin".
15	(Zhuang, Liu, and Xiong 2018)	2018	"A virtual, dynamic model in the virtual world that is fully consistent with its corresponding physical entity in the real world and can simulate its physical counterpart's characteristics, behaviour, life, and performance in a timely fashion".
16	(Sierla et al. 2018)	2018	"Digital twin: a near-real-time digital image of a physical object or process that helps optimize business performance".
17	(Kunath and Winkler 2018)	2018	" The Digital twin of a physical object as the sum of all logically related data, i.e. engineering data and operational data, represented by a semantic data model."
18	(Tharma, Winter, and Eigner 2018)	2018	"Digital twin of a real distributed product is a virtual reflection, which can describe the exhaustive physical and functional properties of the product along the whole life cycle and can deliver and receive product information".
19	(Eisentrager et al. 2018)	2018	"A digital twin is a digital model of a real object containing lifecycle records and dynamic status data, which are synchronized in real-time. The model will be used to gain knowledge that can be transferred to the real object".
20	(Negri et al. 2019)	2019	"An integrated simulation of a complex product/system that, through physical models and sensor updates, ontol twin".
21	(Biesinger et al. 2019)	2019	"A digital twin is defined as a realistic model on a current state of the process and behaviour of real objects with its structure and elements that are connected to it".
22	(Kabaldin et al. 2019)	2019	" A set of mathematical models characterizing in real-time the different states of the equipment, the technological processes, and the business processes in production conditions".

components of the digital twin: real-time interaction and the replication of physical asset functionalities in the virtual space etc.

For this paper, the digital twin concept can be applied within the manufacturing industry primarily at three levels, namely: product, unit/systems and system of a system (SoS)/shop-floor levels. These virtually represent the integration of process, raw material, tools/equipment, finished product and services, including all static and dynamic compositions of the production system (Qi et al. 2018a). Virtual models used for a digital twin can include the following physical models (geometric, performance, simulation, etc.), relational rules and behaviour models that reflect the state, characteristics, behaviours and performance of its physical entities (Cheng et al. 2018). They can be used for simulations during virtual commissioning, monitoring, diagnostics, prediction and control of the state and behaviour of its twin to support decision-making in the development and operation phases of the product, as well as reflect information continuity throughout the product lifecycle (Schleich et al. 2017; Haag and Anderl 2018). Figure 4 shows increased usage of the concept within the manufacturing sector.

3.3.1. *Digital twin of a product*

The digital twin of a product is simply its digital construct mapping the individual product in the virtual space. Its level of functionality and comprehensiveness is dependent on the physical twin and intended use (Tao et al. 2018; Haag and Anderl 2018).

3.3.2. Digital twin at a unit/system level

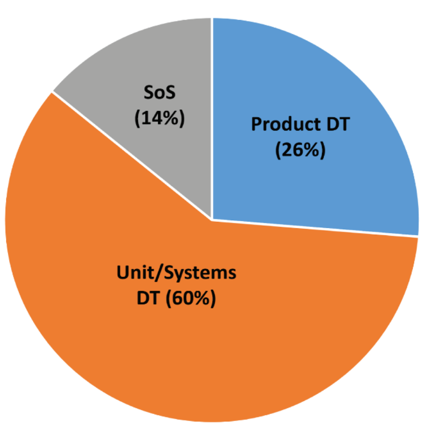
A digital twin at a unit level of the CPS systems is at its smallest possible granularity. Such small units include components and equipment (e.g. computer numerical control (CNC) machines, robots etc.), materials (transport facilities like automated guided vehicles (AGV) and other value-added raw materials), and smart environments (Kritzinger et al. 2018). The digital twin at a system level is an integrated data-oriented virtual replica of all necessary process elements. This includes all unit-level digital twins of manufacturing equipment, material flow, operating systems, human resources, and other value stream elements (Blum and Schuh 2017; Qi et al. 2018a). At the system level of a shop-floor, models considered include production capability models for production capability and characterisation, process models to link process-related parameters to product design attributes and mirror the interaction between a product and the model of its corresponding production process model (Cheng et al. 2018).

3.3.3. Digital twin at an SoS level

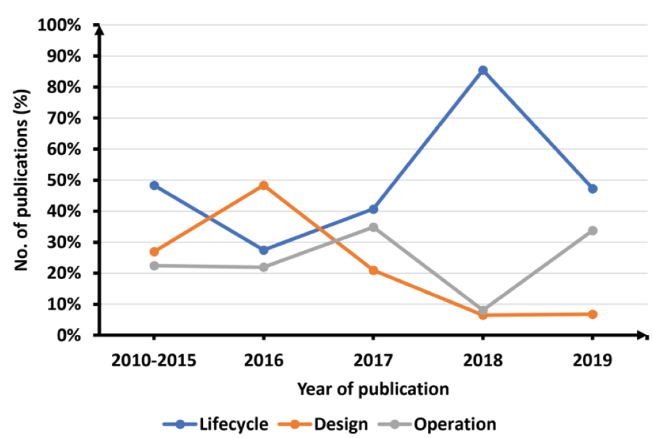
The digital twin smart service platforms can be used to achieve collaboration between system-level CPSs and digital twins. This could be a collaboration within a factory site where production lines can interact or different factory sites. Such an integrated platform enables the integration of the various lifecycle processes of a product, data and resources. This is an enabling environment for cross-systems and cross-platform interconnection and interoperability and optimisation of servitisation (Qi et al. 2018a).

Figure 4(a) shows more use of the digital twin to support the unit/systems level. Figure 4(b), demonstrates the publications trend in the last 10 years. A large number of publications in 2018 highlight the use of digital twin in physical asset's lifecycle, enabling an enriched digital twin database built right from the design stage to be available all through its lifecycle (Jones et al. 2020). Publications in 2019 show an increased discussion of the digital twin in the operational phase with a focus on simulation and optimisation using real-time operational data. There is a congruence amongst authors that digital innovations like sensor data fusion, IoT, edge and cloud computing technologies, deep learning and machine learning in Artificial intelligence, big data analytics, faster algorithms, increased computational power and the availability of more operational data are triggers for the modification of the expectations of the concept (Lu and Xu 2018; Scaglioni and Ferretti 2018; Zhang et al. 2019a).

Analysis of the articles identified six key functionalities inherent in the digital twin applications namely, prognostic and diagnostic analyses, simulation (online and offline), control, monitoring/supervision and optimisation (Figure 5) (Martinez et al. 2018; Zhuang, Liu, and Xiong 2018; Zhang et al. 2019a, 2019b). As seen in Figure 5, in recent years, there has been more



(a): Percentage of publications based on digital twin type



(b): Trend of the digital twin applicability in process/product lifecycle phases

Figure 4. (a): Percentage of publications based on digital twin type. (b): Trend of the digital twin applicability in process/product lifecycle phases.

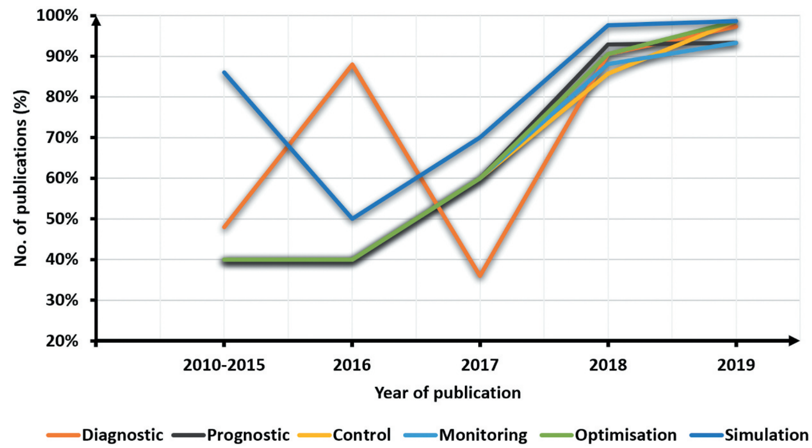


Figure 5. Digital twin functionalities.

acceptance of the potentiality of the digital twin concept to provide all six functionalities. Figure 5 demonstrates a steady rise in both simulation and optimisation is as a result of the availability of more factual data (operational data) for simulation and a better understanding of the physical asset through mirrored/factual virtual representation/analysis.

3.4. Current industrial understanding and applications

The disparity in the understanding of the digital twin vision in the industry is seen in its application, as shown in Table 2. It is being used along with various phases of the product lifecycle, interconnect business partners and customers. Microsoft Corporation views the digital twin concept as a business transformation strategy (Microsoft 2017).

3.5. Related work on digital twin frameworks in manufacturing

This section reviews the proposed digital twin frameworks from the literature. Greives' standard architecture for a digital twin model consists of a physical asset, virtual replica and connection which is sufficient to establish a cyber-physical interaction (Grieves and Vickers 2016). This architecture in some use-case has been extended up to a six-dimensional framework by the inclusion of digital twin data and services (Tao et al. 2018; Zhang et al. 2019a:2019b). These enable the fusion and evolution of both physical and virtually generated data and the addition of analytical functionalities to the digital twin.

Tao et al. (2018) presented a digital twin-driven product design (DTPD) framework. This serves as a guide on the creation of a product digital twin

Table 2. Table of companies' views and application purpose.

Ref	Companies	View	Purpose
(Schleich et al. 2017)	Parametric Technology Corporation (PTC)	Real-time connectivity between the virtual and physical world	Provide efficient after-sales services using digital twin data.
(Cheng et al. 2018)	General Electric (GE)	Modelling of the current state of its physical twin	To improve the efficiency of performance and health forecast of products throughout their lifecycle
(Microsoft 2017).	Microsoft Corp.	A business transformation strategy	Integrate the business supply chain
(Schleich et al. 2017)	Dassault Systèmes		Improve product design performance
(Schleich et al. 2017)	TESLA Inc.		To achieve synchronous data flow between vehicles, factory and other companies.
(Cheng et al. 2018)	NASA	Interconnection of both physical assets and an equivalent virtual replica of the physical system	Used for fault prediction and validation of related systems
(Cheng et al. 2018)	U.S. Department of Defence	An integrated simulation virtual replica of the physical asset	Used for health maintenance of aerospace crafts
(Schleich et al. 2017)	Siemens	Virtual models of a physical production system	Establish a connection between virtual and physical space to capture the digital process of products from the design stage to manufacturing to improve efficiency and quality
(Shubenkova et al. 2018)	Predix Asset Performance Management (Predix APM)		Service based platform for industrial-grade analytics for operation optimization and performance management
(Shubenkova et al. 2018)	DXC Technology		A software platform used for hybrid car manufacturing

and the utilisation of its generated knowledge in the product design process. Zhang et al. (2019a) proposed a data and knowledge-driven digital twin framework for a manufacturing cell (DMTC). This supports an autonomous manufacturing cell using data for the perception of manufacturing problems and knowledge for solving identified problems. This has five-dimensional space namely the physical, digital, data, knowledge and social space. This framework is expected to support self-thinking, self-decision-making, self-execution and self-improving. Cheng et al. (2018) also present the aims of a smart factory for the fourth manufacturing generation. In this case, the digital twin concept is used to achieve physical connection and data collection, virtual models and simulations, data and information technology systems integration and lastly, databased production operations and management methods. These expectations are also embraced by other authors like Ellgass et al. (2018), Qi et al. 2018a) and Zhang et al. (2019a).

Notably, Stark et al. (2019) applied information factories in the development and operation of a digital factory twin. They proposed an eight-dimensional digital twin model. Four of these dimensions namely integration breath, connection mode, update frequency and product lifecycle characterise its environment and the other four dimensions: CPS intelligence, simulation capabilities, digital twin model richness and human interaction describe its behaviour (capability richness expressed in levels). Lu et al. (2020) presented a digital twin reference model with three components, namely, an information model, a communication mechanism and a data processing module. The information model has two subtypes: a model for a product digital twin and another for a production digital twin.

Existing digital twin frameworks in literature do not consider the modelling of the interaction between the product and its production processes (Grieves and Vickers 2016; Tao et al. 2018; Zhang et al. 2019a:2019b). As a result, they do not present the integration of the product and process digital twins in this perspective. A CPPS integrated product-process digital twin with logically connected data/control/resources is a suitable digital platform where the interaction of the product and process models is used to enhance the control/management of the physical asset performance and product quality.

3.6. Cyber-physical integration using other concepts similar to the digital twin

In the last decade, other digital solutions for an integrated manufacturing environment have been reported in the literature, for example, the Cyber-physical system (CPS), Digital mock-up unit (DMU), Symbiotic simulation and the Product avatar. They all attempt to connect the physical space with the virtual world. The CPS with sensing, computation, control and communication capabilities attempts to achieve physical asset integration (Ward et al. 2021). The DMU, a system engineering 3D modelling process developed based on CAX (CAD/CAE/CAM) technology uses computer simulations as a replica of the actual mock-up (Zhang and Li 2013; Ríos et al. 2015). They can imitate the geometrical, physical and behavioural characteristics of the actual product mock-up thus providing real responses to exterior prompting as would the actual mock-up. Like the DT, real-time interactions with the product enable immersion sensory perception (Ríos et al. 2015; Tao et al. 2019(2)).

The symbiotic simulation system, birthed under discrete event simulation (DES) draws inspiration from symbiosis in biology. It emphasises a mutually beneficial close relationship between a physical system and its simulation system (Mitchell & Yilmaz 2008). Like the DT, the simulation system has access to real-time sensor operational data from the physical system. With this, highly accurate simulations of the physical system are carried out and in turn, the physical system benefits from the decisions made based on the outcome of the simulations of several scenarios representing different operational decisions (Mitchell & Yilmaz 2008). The product avatar concept with no explicitly significant difference from the DT concept focuses on user-oriented product formation. Like the DT, it also considers sensor data and the physical product is digitally represented using several models (Ríos et al. 2015). In addition to integration, the digital twin offers the advantages of inclusiveness of communication, interaction and collaboration between the virtual and physical space (Tao et al. 2019(2)). It serves as a representation of both the digital and physical properties of the current and future state of the product, equipment or process (Schroeder et al. 2016).

3.7. Cyber-physical integration using the digital twin concept

Cheng et al. (2018) presented the aims of a smart factory for the fourth manufacturing generation and analysed them in four contexts namely (i) physical integration and data collection, (ii) digital/virtual models and simulations, (iii) data and information technology systems integration and lastly, (iv) data-based production operations and management methods. Viewing the capabilities of the digital twin from these perspectives constructs a more vivid picture of how it supports integration, flexibility and collaboration within the smart manufacturing environment.

3.7.1. Physical asset integration and data collection

The creation of ubiquitous interconnections between physically separated elements/subsystems of a production system based on a collaborative and context-awareness initiative will support data collection, interaction and interoperation within an integrated environment. Such an integrated operational environment is obtainable using the CPPS concept.

3.7.2. Digital/virtual models and simulation

The creation of multi-dimensional models by the integration of faithful-mirrored virtual models of both the product/processes systematically constructed using all necessary data (both engineering and operational data) within a closed-loop bidirectional network with the physical assets will contain geometric and physical properties models of elements, response models of behaviours and logical models of relationships. This will enable reliable and synchronous real-time systems/models co-simulation, correction, modification and control.

3.7.3. Data and information system integration

The virtual models provide the mechanism (relational rule model) for a methodical integration and unambiguous fusion of cyberspace (all elements/flows/businesses-covered) data with data perceived from the physical world. This mechanism will support the dynamic generation and iterative co-evolution of models and big manufacturing data.

3.7.4. Data-based production operations and management methods

Physical-cyber consistency and synchronisation present an avenue for more effective utilisation of generated data for value creation through collaboration. Operational optimisation in factories can be improved through the integration of data-driven services and interdependencies of applications allowing on-demand matching and utilisation of services.

3.8. Summary of literature review

There is a growing acceptance of the digital twin concept as an essential driving force/element for the fourth manufacturing generation. There is yet no common framework for a digital twin model but it has found applicability in the various stages of the product/process. The integration of ICT technologies and AI into production systems has paved the way for a lot of possibilities with the digital twin in manufacturing. Six key functionalities inherent in the digital twin applications were identified: prognostic and diagnostic analyses, simulation (online and offline), control, monitoring/supervision and optimisation.

The digital twin concept initially was applied to product design. In recent times, it is perceived to encompass the entire business value chain resulting in digital twins of products, production process, system performance and services. The current vision of the digital twin concept in manufacturing supports the realisation of an integrated, flexible and collaborative manufacturing environment. Supported by a closed-loop bidirectional communication network, it promotes asset-twin co-evolution through real-time interaction, control and convergence in three key areas: within the physical space, between the physical and virtual spaces and between historical and real-time data.

4. Digital twin framework for smart manufacturing

This section proposes a digital twin framework based on the integration of both the product and process digital twins. The methodology for the proposed framework is discussed in section 4.2, the actual framework is described in section 4.3 and the benefits of the proposed framework for manufacturing systems are discussed in section 4.4.

4.1. Background

This paper advocates for the integration of both product and process digital twin to support cyber-physical production systems (CPPS). Integrating production systems with ICT technologies and employing artificial intelligence in manufacturing systems transforms traditional production systems into what is now known as cyber-physical production systems (Negri et al. 2019). The CPPS paradigm with more ICT enhancements, scalable modular structures and distributed control introduces autonomous integrated, adaptable production systems that shortens engineering time in production processes and cost of mass customisation. (Qi et al. 2018).

Lu et al. (2020)'s model talked about the product and the process information models. This work extends this idea to an integrated product-process digital twin concept to harness the benefits in modelling the logical interaction between the product and its production processes. This interdependence between the product and its production processes modelled as a logical interaction is presented as the collaboration mechanism between the product/process digital twins and physical assets. This mechanism during production would create new digital twin collaborative functionalities that would improve both digital twins performances. Its benefits are further explained in subsection 4.4.

4.2. Methodology for implementing the proposed framework

This subsection discusses the integration of the product and process digital twins and also, the approach used in utilising the dynamic interaction between the product and its production processes in supporting flexibility and product customisation.

4.2.1. Integrating the product and process digital twins

The dynamic interaction between the product and its production processes is shown in Figure 6 . Modelled as a collaboration mechanism, this logical interaction can be bidirectional where the process digital twin provides data (value addition) for building the product digital twin and the product digital twin provides process configurations relative to predefined product specifications.

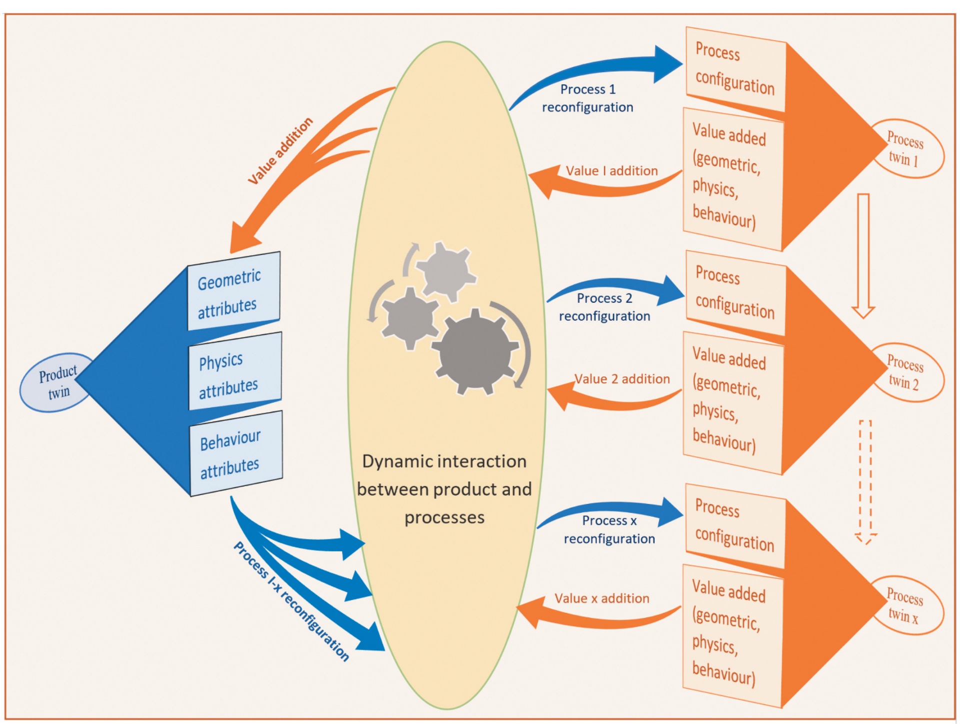


Figure 6. Integrated product-process DT showing the interaction between product and process twins.

This mechanism can be implemented using a relational rule model. The integration of the product and process is achieved using the steps below:

- Stage 1: Carry out a logical mapping of the product attributes to the respective process services that generate them. This is done by identifying the value-added services that build the product and its attributes.
- Stage 2: Develop the process and product models. This can be done on the same or separate digital platform(s). Using the same digital platform eliminates the challenges/constraints with communication links between heterogenous platforms.
- Stage 3: Develop a relational rule model that logically implements the interaction between the process digital twin services and the product digital twin attributes. This establishes the logical connection between the product digital twin and the process digital twin. It maps the product attributes to the respective service configurations and manages the logical integration of the product and process data to create an integrated product-process digital twin information model.

The product twin based on product specifications can influence the configuration of the production system through the process digital twin. On the other, the production system through the process digital twin can provide the product data needed to mirror the physical product. With model standardization, heterogeneity in generated data can be eliminated between the digital twins. This would enable the integration of product and production data/resources. This collaboration would improve each other's performance and in general the physical asset. For instance, using the product digital twin, the product quality can be monitored during production hence reducing the production cost related to quality assurance activities.

4.2.2. Product-centric Control Method

Product-centric control is an emerging agile method that is intended to simplify material handling, control, product customisation and information usage within the supply chain. It uses unique identification for all associated resources which are linked to control instructions. While the product is in production, it directly requests material handling and processes from service providers within the supply chain (Lyly-Yrjänäinen et al. 2016; Sierla et al. 2018). To promote product customisation and production flexibility using the proposed digital twin framework (section 4.3), the product-centric control method is adopted to enable the product twin to influence its production (Eisentrager et al. 2018; Sierla et al. 2018). Product specifications defined in the virtual space can be linked to process configurations such that processes/machines can be configured to handle customer variation. This could involve the arrangement of raw materials, the sequence of processes and resources in general (Sierla et al. 2018). Useful time is saved as setup time due to some manpower reorganisation/reconfiguration of the production layout is reduced.

Figure 7 shows the path (a-b) used by the virtual product to trigger the configuration of the physical system. When the product is selected, its specifications determine the configuration of the virtual process model which in turn triggers the configuration of the physical system.

4.3. Proposed digital twin framework for manufacturing systems

This section presents the proposed digital twin framework that supports the integration of both product and process digital twins. The framework proposed (Figure 8) in this section comprises six components: (a) Integrated physical assets, (b) Integrated faithful product/process virtual models, (c) Intelligent layer, (d) Data layer and (e) Enterprise layer. Like the other frameworks highlighted above, this framework supports the identified six key functionalities inherent in the digital twin applications listed in section 3.3. This framework attempt to address the following key issues: (1) The integration of all interconnected physical elements, (2) Ultra-high synchronisation of the virtual space with the physical space that supports real-time interactive simulation and (3) Data fusion covering all elements, flows, business services and data-driven and application-oriented services integration (Yun, Park, and Kim 2017; Kritzinger et al. 2018).

(a)Integrated physical assets: This refers to a composition of all related manufacturing entities of the system interconnected, monitored and managed using advanced automation equipment like microcontrollers, programmable logic controllers (PLCs), human-machine interface (HMI) for human inclusion as an asset, computer-aided controls

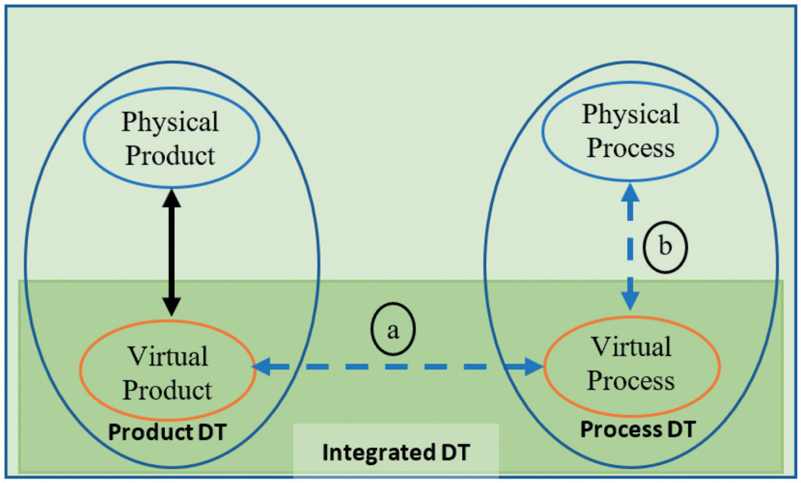


Figure 7. An integrated product-process DT showing the path used by the product twin to influence process configuration using the product-centric control method.

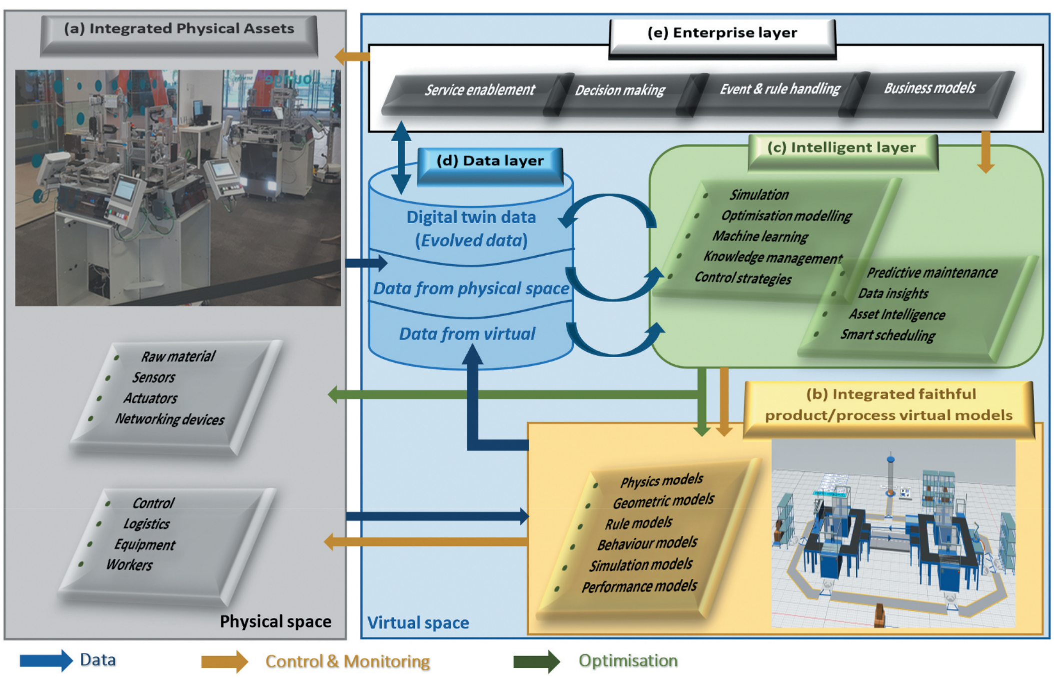


Figure 8. Digital twin framework of a manufacturing system showing closed-loop interaction

and technical processes; information technologies like sensors, radio frequency identification (RFID), network infrastructures like servers, intelligent routers, switches, TCP/IP/Ethernet/OPC_UA/MTConnect protocols, etc., and software (Qi et al. 2018b). This enables the automation of repetitive processes that move and exchange information across the system, enabling process execution, control, data perception and transmission (Zhang et al. 2019a). Asset here could include passive resources like work-in-progress (WIP), active resources like equipment-CNC machines, robots, workforce, transports, smart environments, smart manufacturing devices, sensors and communication gateways (Zhang et al. 2019b).

(b) Faithful virtual models: This involves the creation of multi-dimensional models by the integration of faithful-mirrored virtual models. These models systematically constructed using all necessary data (both engineering and operational data) should contain models of geometric and physical properties, models of elements, response models of behaviours

and logical models of relationships (Tao and Zhang 2017). These models in a closed-loop network with their physical twin will enable reliable and synchronous systems/models co-simulation, correction, modification and control. The level of model granularity is defined by the intended functionality and level of fidelity. Well defined properties of the physical system can be modelled using engineering principles while dynamic behaviours can be modelled using stochastic models which are maintained using operational data. This approach would enable the evolution of the virtual models to reflect the current state of the physical twin, support diagnostic, prognostic and prescriptive analysis. More recent simulation software has been developed to support digital twinning with the inclusion of OPC_UA interfaces with standardised data exchange, better streaming/storage/processing of data and communication. For example, Siemens Tecnomatix equipped with 3D visualisation and OPC_UA connectivity can be used for real-time supervision, control and visualisation of the physical twin.

(c) Intelligent layer: The physical connection and collection of data allow for the creation of ubiquitous interconnections between physically separated elements/subsystems of a production system and virtually separated models/algorithms. This layer serves as the brain of the digital twin. It integrates all layers of the digital twin using a constructive collaborative and context-awareness initiative that supports data collection, interaction and interoperation within an integrated environment (Rosen et al. 2015). Programs suitable for specific functionalities are incorporated to perform at a certain level of autonomy. Even when distributed control and computerisation is used to improve system speed and reliability, these algorithms/models enables every member to become aware of the existence of each other and their operability. This layer equipped with artificial intelligence, machine learning algorithms and accessible to both enterprise, engineering and operational data can be seen to generate information needed to support production and enterprise decisions (Macchi et al. 2018). Thus this presents the digital twin as a supportive decision-making system with dynamic knowledge built through a continuous accumulation of its interaction.

(d) Data layer: Data and information system integration is achieved at this layer, enabling a systematic integration and unambiguous fusion of cyberspace (all elements/flows/businesses-covered) data with data perceived from the physical world. This layer will support the dynamic generation and iterative co-evolution of models and big manufacturing data (Zhang et al. 2019a). With the interaction of the physical space with the virtual space, virtual information/models can be updated and operated using real-time data. The integration of physical and virtual data can be achieved through the co-evolution of models/data using algorithms to generate information instances of the current status of the physical asset or results of simulation analysis (Tao, Zhang, and Nee 2019). This can then be used to update/reconfigure virtual models or control/influence the operation of the physical system. Being able to generate and access standardised data makes accumulated information accessible to all connected entities. Special database middleware providers like Oracle and Microsoft provide platforms for data processing, security and storage.

(e)Enterprise layer: Based on the reference model (RAMI4.0) of I4.0, the enterprise layer falls under the hierarchy levels. This layer using service systems such as enterprise resource planning (ERP) and customer relation management (CRM) enables data-based production and management methods like service enablement, business models and business decision-making, event and rule handling etc (Cruz Salazar et al. 2019). Cyber-physical consistency and synchronisation present an avenue for more effective utilisation of generated data for value creation. Operational optimisation in factories can be improved through the integration of data-driven services and interdependencies of applications allowing on-demand matching and utilisation of services (Negri et al. 2019). The internet of things (IoT) which allows the connection of people and things using internet services/networks and edge/cloud computing are potential technologies that can extend the vertical integration of this layer across the business chain (Brenner and Hummel 2017). It provides service and interface layers needed to seamlessly include contributions made by customers and suppliers to the activities/decisions made within the system (Qi et al. 2018b).

4.4. Benefits of the proposed framework

The proposed digital twin framework offers the following benefits:

4.4.1. Integration

This framework has a generic structure applicable to any manufacturing system, is expandable, enables fast and easy integration of new resources (physical and virtual) and lastly, is robust to uncertainties peculiar to the manufacturing system. Considering the industrial automation pyramid from ISA 95, this digital twin framework attempts to integrate (vertically and horizontally) all layers by adopting standardised communication like the TCP/IP/Ethernet standard, uniform data formats like the JSON format and predefined protocols like the OPC_UA and MTConnect protocol (Cruz Salazar et al. 2019). This supports the real-time bidirectional connectivity of IoT within the production system, operational data generation, storage and use, bidirectional control and online/offline simulation. All six layers of the framework are applicable to both product and process digital twins thus, it supports the integration of both product and process digital twins which in extension promotes product customisation, process flexibility and a supportive decision-making system.

4.4.2. Interconnectivity

The digital twin framework can be used to tackle interconnectivity challenges arising due to the lack of interaction and interoperability between disconnected related industrial sites, independent digital models, non-self-controlled applications and isolated data silos created within the physical workspace and virtual information space (Blum and Schuh 2017; Cheng et al. 2018). The use of standard data formats and communication specifications like the OPC_UA and MTConnect protocols promotes uniformity in data. Also, the use of IoT, cloud computing, machine learning algorithms and internet technologies like the 5 G network to generate, process and distribute relevant information enables communication and collaborations along the supply chain (Negri, Fumagalli, and Macchi 2017).

4.4.3. Production flexibility and product customisation

In an integrated product-process digital twin platform, the virtual product influences its production as product specifications defined in the virtual space influences the configuration of equipment/production layout. When product customisation is automated, it reduces human intervention and reduces setup time during the reconfiguration of the production setup to include customer demand variations in either the same product or when changing products (Sierla et al. 2018). It expedites a new era of production where last-minute changes to production and flexibly respond to disruptions and failures caused by suppliers.

4.4.4. Analytics

Data analytics has been a formidable tool used for evaluating past incidences and the prediction of the future state (Schuh and Blum 2016). As shown in Figure 9, the proposed digital twin framework enables the inclusion of both operational and environmental data for analytics (Rosen et al. 2015; Catapult 2018). These additional data reflect the real state of the manufacturing infrastructure. The inclusion of such information in analyses reduces the impact of presumption or engineering estimations. This would facilitate the enhancement of manufacturing efficiency leading to a more lean and competitive establishment (Onaji et al. 2019; Schuh and Blum 2016).

4.4.5. Supportive decision-making system

Built on real-time operational data, the CPPS is capable of making its own decisions about its future or support external decision-making systems (Zhang et al. 2019a; Zhou et al. 2019). Mirroring the physical environment within the digital space enables analyses of the interactive dynamism between the product, process and environmental factors resulting in a timely response to such changes. Based on analytical outcomes, the digital models connected to the control system can trigger necessary control commands. This is of significant influence on product and process management and optimisation (Weyer et al. 2016; Jones et al. 2020). The digital

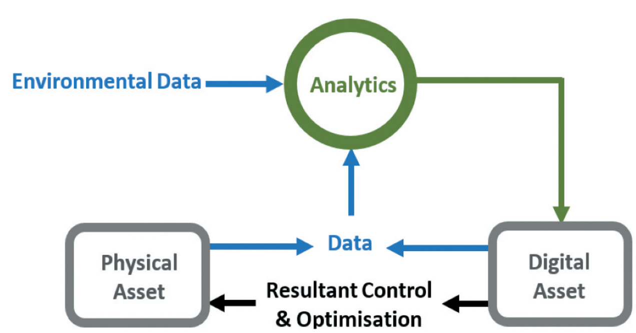


Figure 9. Analytics in an interactive digital twin. From: (Catapult 2018).

twin integrated platform enriched with a standardised semantic description can retain relevant data throughout its lifecycle (Schuh and Blum 2016; Cheng et al. 2018).

5. Case studies

This subsection presents three case studies. The authors were involved in the development of the first two case studies based on the proposed digital twin framework in Section 4. These case studies present applicative evidence as a contribution to reinforcing the diversified use of the proposed digital twin framework/ideas to encourage more investment and further adoption in existing industrial infrastructures. The first case study is based on the Festo cyber-physical smart factory, the second is based on a Pharmaceutical continuous crystallisation system and the third is based on a Virtual X-Ray of electric motors. The first and second are based on facilities within the University of Sheffield and reflect systems/structures within the manufacturing industry.

5.1. Discrete-time CPPS based on the Festo cyber-physical (CP) smart factory

5.1.1. The Festo cyber-physical smart factory

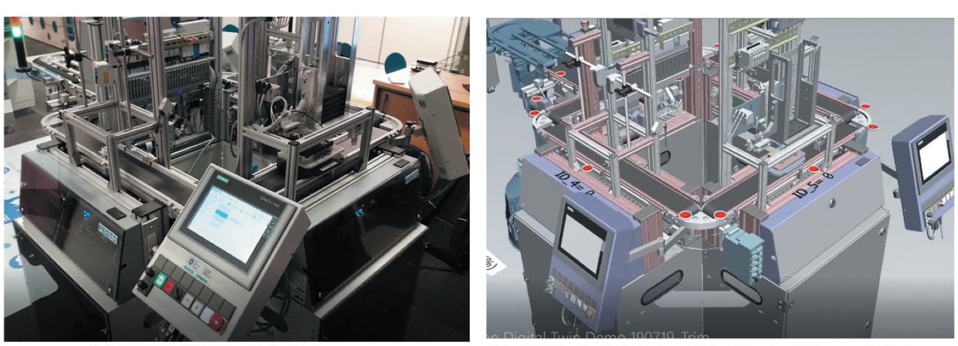
Figure 10a is the integrated physical asset. It is an Industry 4.0 compact CPPS used for teaching and the development of smart industrial automation-based skills. Its resources have been interconnected and monitored over a TCP/IP/Ethernet/OPC_UA network infrastructure using sensors and RFID technologies. It adopted a distributed control with each module having its Programmable logic controller (PLC). The system is managed using the manufacturing execution system (MES) linked to a database (ACSE 2018). It is composed of two production Islands and a logistics network of conveyors, carriers for conveying the flow entity and an autonomous vehicle (Robotino). The workstations are built with six stations and two transfer bridges (Table 3). Further details about the Festo CP smart factory can be found in (ACSE 2018).

Table 3. Festo CP smart factory stations and the task each performs

Station	Task
Top case (Station 1)	Place the top cover of the phone on the carrier
Measuring (Station 4)	Inspects the workpiece on the carrier
Bottom case (Station 5)	Loads the carrier with the bottom cover of the phone
Press (Station 6)	Couples the top and bottom cover by pressing them together
Heat tunnel (Station 7)	Heat workpiece to a predefined temperature
Output station (Station 8)	Removes finished product from the production line
Bridges (Station 2&3)	Transfer terminal the workstations
Robotino	Transfer product between workstations

Production orders are made from the MES. A workpiece is introduced at the 'Top case' station. This is inspected at the 'Measure' station and then transported through the rest of the stations: 'Bottom case', 'Press', 'Heat tunnel', 'Bridges' and 'Output' stations in that order. At the 'Output' station the finished/rejected product is removed from the production line. Table 3 gives a list of the Festo CP smart factory stations and the task each performs.

The project objective is to build a supervisory digital twin that supports process monitoring and experimental analysis. This model is fed with live streams of



(a): Festo CP smart factory (b): DES digital twin of the Festo CP smart factory

Figure 10. (a): Festo CP smart factory. (b): DES digital twin of the Festo CP smart factory.

data from the sensory devices on the physical asset. This data can be used to investigate bottlenecks in the processes and their impact on the final product.

5.1.2. Methodology

The methodology used in developing the digital twin of the Festo CP smart factory involved the following steps: conceptual model design, virtual model development, control panel development, data layer development, intelligent layer development and lastly, verification and validation process. This approach allows the gradual build-in of the complexity of the existing physical system.

(a) *Conceptual model design*: This involved the definition of the project objective, system definition and the construction of a conceptual model. This entails the identification of the processes and product attributes to be digitised, physical data, process behaviour/functionalities to be modelled/visualised and lastly, investigate the accessibility of the existing system architecture to identify how it can be digitally assessed.

(b) *Virtual models development*: This includes the process and product simulation models whose granularities were defined by the functionalities and modular structure identified in the first step. This involved building the 3D models, implementing the relational rule model that established the interaction between the product attributes and process twins services, control codes and simulation flow. The Siemens NX was used to build a 3D CAD model (Figure 10), and the Tecnomatix plant simulation (a platform for agent-based/ discrete event simulations(DES)) was used to construct the DES model of the processes (Figure 11 (b&c)). The software used here were selected because it got impressive visualisation, the OPC_UA protocol and most importantly can be used for analytics to achieve logistic process improvement, material flow optimisation and efficient resource usage (Onaji et al. 2019). This stage also took care of the creation of the OPC_UA interfaces used to establish the bidirectional communication between the physical system and virtual platform.

(c) *Control panel development*: This stage involves the addition of control elements like push buttons linked to control instructions/algorithms of the virtual model, input, output/display elements for data. These graphic user interfaces (GUI) elements control the virtual simulation and online connection to the physical system.

(d) *The data layer development*: This involves the inclusion of data storage elements like tables, global, local variables and interfaces for visualising information. Both operational and virtual data were stored for analytical use.

(e) *Intelligent layer development*: This involves the inclusion of algorithms to generate virtual data, process data to provide required information during controlled experiments. This extracted information can be used to manage or improve the operation of the physical system.

(f) *Model verification and validation*: These steps are carried out intermittently throughout the development stages. All logic and modelled operations are debugged and tested to ensure they are error-free and built following the project design.

5.1.3. Developed DES digital twin model of the physical processes

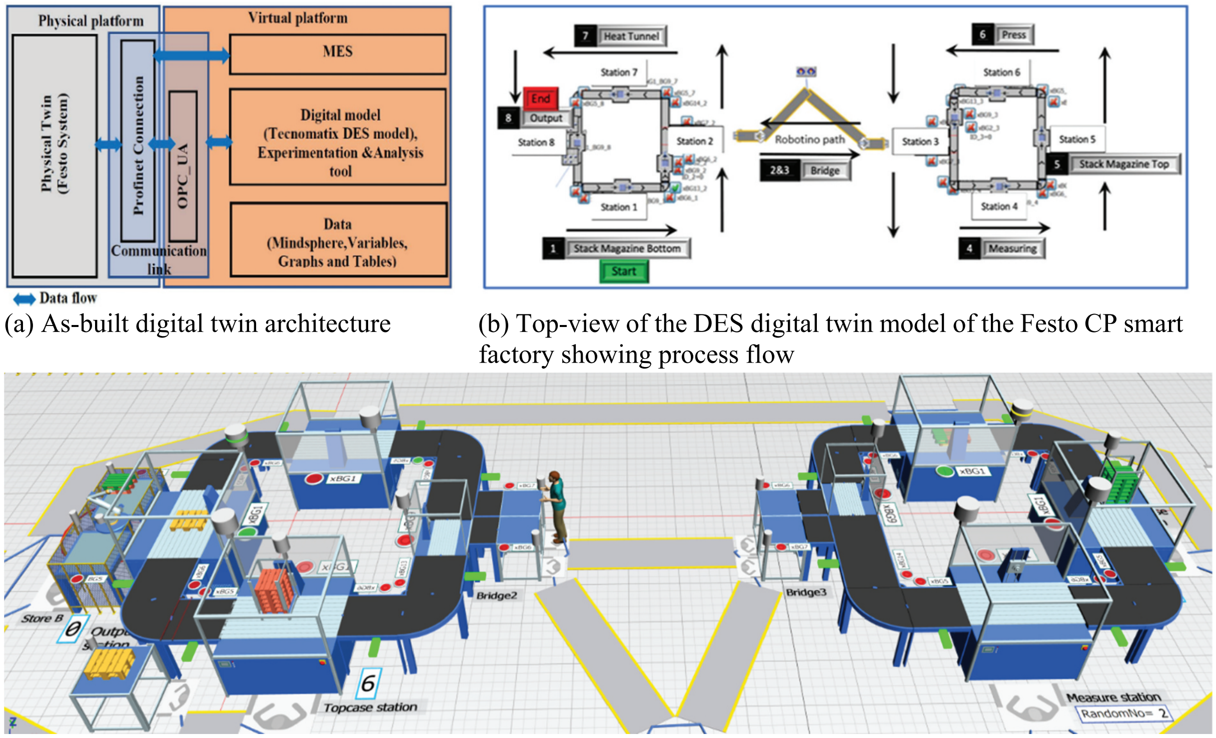
The developed DES digital twin model of the Festo CP smart factory (Figure 9)), inherits predefined behaviours and interaction of the system with its control algorithms developed to manage the material flow. This was achieved using the predefined material flow objects (Table 4) of the simulation software. Figure 11(a) shows the as-built digital twin architecture, Figure 11(b&c) shows the DES digital twin of the Festo CP smart factory showing process flow.

5.1.4. Developed DES product digital twin model

The product is a simple composition of a top and bottom case for a phone. The process flow analysis provided details on the services and their weight on the attributes of the product. This information is

Table 4. Main objects of the Festo digital twin model.

S/no	Material flow objects	Number	Justification
1	Stations	8	Process execution
2	Footpath	4	Robotino path
3	Conveyors	16	Transport-conveyors
4	Operator	1	Robotino
5	Workspace	2	Robotino docking stations
6	Checkbox	12	Position sensors at stations and bridges
7	Source	1	Part creation and intro into the system
8	Store	1	Product from the system is stored for removal



(a) As-built digital twin architecture

(b) Top-view of the DES digital twin model of the Festo CP smart factory showing process flow

(c) 3D view of the process DT model

Figure 11. Overview of the developed digital twin of the Festo CP smart factory.

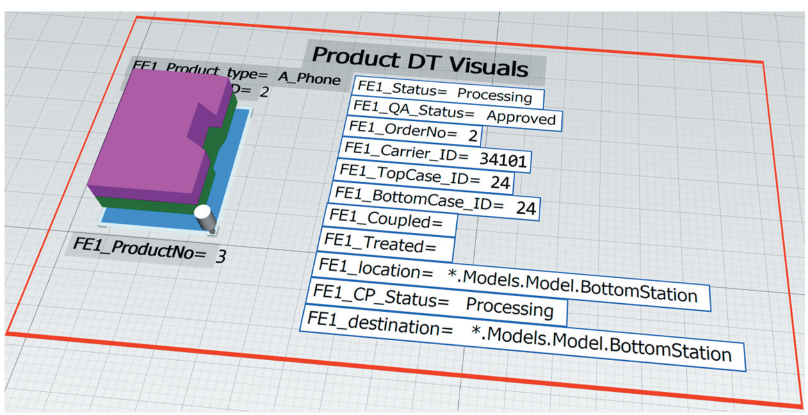
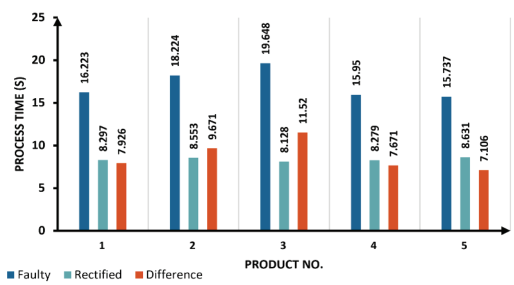


Figure 12. Product digital twin visuals.

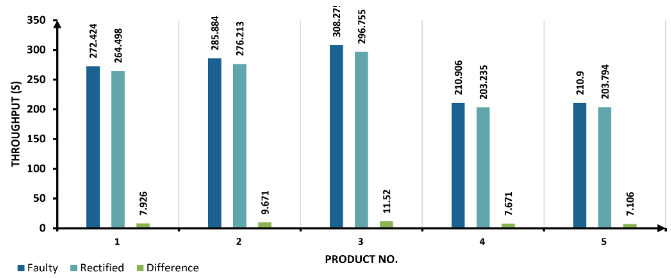
conveyed along the production line using RFID technology mounted on the carriers. The RFID chip on the carrier enables a progressive transmission of the product data as the physical product is processed. This enables a real-time synchronised update of the product digital twin. Figure 12 presents the product digital twin visuals: a geometric model and extracts of its information model.

5.1.5. Results and discussion

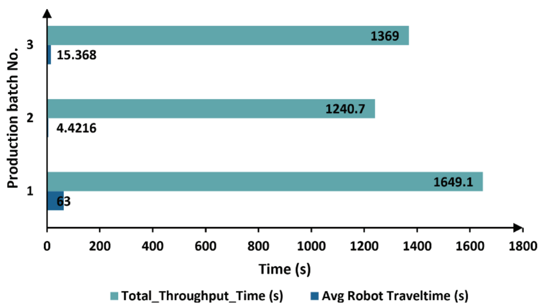
Experiments carried out revealed more details on identified bottlenecks and enabled corrective maintenance and strategy proposition to improve production. Identified bottlenecks included increased friction between carriers and conveyors, delay in unloading finished products from the 'Output' station, waste of process time on rejected workpieces and lost process



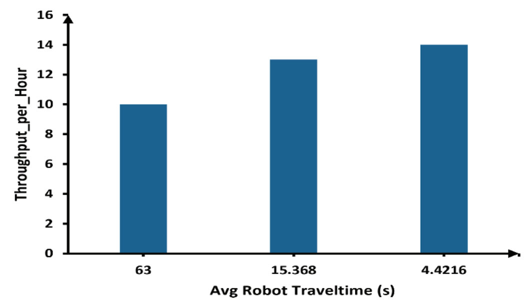
(a): The impact of travel time on process time



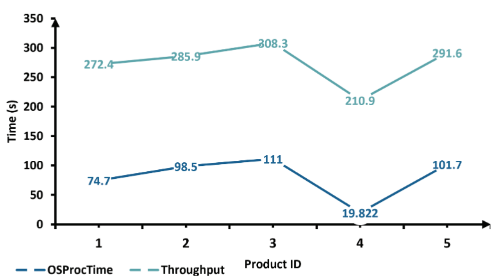
(b): The impact of travel time on total throughput



(c): Impact of robot travel time on total throughput time



(d): Impact of robot travel time on total throughput per hour



(e): The impact of the output station storage capacity on throughput

Avg. robot travel time (s)	Total throughput time (s)	Throughput per hour
5.467	16:36.0	18
10.467	17:26.0	17
15.467	18:16.0	16
20.467	19:06.0	16
30.467	20:46.0	14

(f) The impact of robot travel-time on the total throughput time and throughput-per-hour

Figure 13. Experimental results revealing more details on identified bottlenecks and system behaviour.

time in heating the 'Heat tunnel' station. Figure 13(a&b) presents the results on the impact on *process time* and *total throughput* by the identified station with increased *travel time* due to friction on its conveyor. Figure 13(c&d) presents results on the impact of using the robot at varying *travel-time* on production *total throughput time*. Figure 13(e) presents results on the impact of the output station *storage capacity* on *throughput*. Lastly, offline simulations were carried out to determine the impact of controllable system parameters on production. Table 13(f) presents the impact of robot travel time on the total throughput time and throughput-per-hour.

These results supported the strategy proposed to keep its store available during production to improve the system throughput and identified optimal system configurations for production.

5.1.6. Benefits of the Festo smart factory digital twin

The digital twin developed has expanded the system's research/experimental capabilities for diagnostic/predictive analyses, investigate business cases and the impact of modification/upgrade decisions, determine optimal production configurations and monitoring. It has also introduced some level of flexibility in teaching/training. The constraint of space and accessibility by a large number of students to the physical system has been tackled using the DES digital twin which can be used offline/online. Current industrial expectations like the Industry 4.0 concepts and technologies can be taught safely especially in covid-19 type situations where physical distancing is vital to safety.

5.1.7. Future work

The next phase of the project would upgrade the current digital twin to an interactive and immersive predictive digital twin, which reflects the complexities and uncertainties experienced in real manufacturing environments and possesses decision-making capabilities. The plan includes an extension of their functionalities to real-time control from the virtual space, including a more robust data layer to implement real-virtual data fusion and product-centric control.

5.2. Continuous-time production system

5.2.1. The pharmaceutical continuous crystallisation system

Figure 14(a) is a highly reliable laboratory environment used for the nucleation and growth of crystals with consistent properties. It consists mainly of a dissolution tank, a chiller and temperature control unit, and a product tank.

Chemical solutions stored in tanks are mixed by passing them through temperature-controlled jacketed tubes with baffles. Oscillation units within the tubes are used to mix the solution while cooling slowly to form crystal as the output of the whole process. Figure 15 presents a block diagram of the continuous tubular crystalliser showing manipulated variables (MVs) and controlled variables (CVs).

The main limitations with the continuous tubular approach of crystallisation are the difficulty in (1) Control due to supersaturation, temperature, mixture, sampling, (2) Implementing process analysis technology (PAT) and (3) Blockages in the tubes due to fouling and sedimentation (Zhang et al. 2017).

5.2.2. Methodology

Using the same methodology in case study one, the digital twin for this system was built using the PharmaMV software (Figure 14(b)). The project objective was to develop a digital twin that supports process monitoring and control, data visualisation, optimisation and multivariant analysis. Its digital twin serves as an integrating platform for the soft sensor, model development and control design. The PharmMV software suite was selected because it meets the regulatory requirements of the pharmaceutical industry. It combines both multivariable monitoring techniques that can be used for root cause analysis and model predictive control functionality for maintenance/improvement of operational efficiency/product quality. Table 5 presents the identified technical requirements needed in the development of the digital twin and what techniques were used to achieve them.

5.2.3. Experimental results

The pharmaceutical continuous crystallisation system digital twin was used in testing the Model predictive controller (MPC) for particle size distribution during the crystallisation process. This was a test to verify the controller design for a bigger system integrated with the same crystallisation system. Figure 16 presents the test results. Based on sample data, the controller's active prediction (dark green) was able to trace the setpoint (red) to yield a stable seed concentration (light green). It also presents the process analytical tools (PAT) connected to the soft sensors used to measure other quality attributes that cannot be measured by the physical sensors.

(a): Crystallisation system

(b): DT of the crystallisation system

Figure 14. (a): Crystallisation system. (b): DT of the crystallisation system.

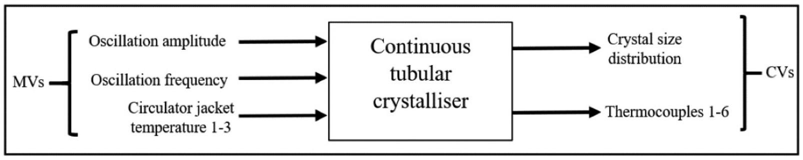


Figure 15. Schematic of a Continuous tubular crystalliser showing its MVs and CVs.

5.2.4. Benefits of the pharmaceutical continuous crystallisation system digital twin

With the digital twin, the following functionalities became accessible to users of the facility: setpoint entry for temperature sensors in the crystalliser tubes, visualisation of crystalliser results like temperature trend, control performances and concentration; crystal size control; availability of data; setting of particle size distribution; setpoint entry for solution concentration value; management of the MPCs controller. From a business perspective, the digital platform as a test and training environment supports experimental analysis without obstructing daily business activities. Also, it reduces the financial burden due to the cost incurred from resources used in physical experiments and training.

To save cost and also increase student accessibility in covid-19 like situations, students now have virtual training/experimentations in product/process development, characterisation, and reverse engineering of new products of high-value manufacturing. For example, a methodological examination of design/modification decisions, investigation of constituent elements/factor and their impact on outcomes. Also, several control techniques can be tested to ascertain, which is best to achieve the desired controllability and productivity, support real-time simulation and emulation of crystallisation processes and products.

Table 5. Technical requirements identified and techniques used in building the digital twin.

S/No	Technical requirements	Actualisation techniques
1	Crystal size distribution	System identification
2	Crystal production yield	PID Control
3	Temperature of the mixing tank	Model predictive control
4	Temperature gradient of crystalliser tubes	Experimental data
5	Flow rate at the incoming of the crystalliser	Identify relevant variable
6	Implement PID control	Implement a Recursive least square (RLS) model
7	Experiment with MPC	State-space controller
8	PRBS system identification	Digital twin mock-up

5.3. Virtual X-ray of electric motors

5.3.1. Digital twin of an electric motor

Developed by Siemens, a virtual X-ray of electric motors is a digital twin that enables monitoring of the real-time performance of an electric motor by utilising thermal simulations to obtain information about temperature distribution inside a motor (Bernard and Sandra 2018). Figure 17 shows a table-sized demonstrator of an electric motor and its digital twin. Researchers at Siemens Corporate Technology (CT), developed this digital twin with virtual sensors to measure and monitor the temperature of the motor components during operation. Using an augmented-reality headset to view the demonstrator of the motor enabled the user to view the simulation of the motor and its interior with a real demonstrator superimposed over it. Colour codes indicated the temperature levels. Detailed information about the temperature distribution inside the motor can enable the operator to decide when the motor is cool enough to be switched on again. This information can help prevent unnecessary downtimes and hence can dramatically lower operating costs.

5.3.2. Methodology

Mathematical models captured the geometry and material characteristics of drive units to create a digital twin of each component. Researchers at Siemens used mathematical reduction processes to derive abstract models. These models could be calculated much faster and with fewer deviations in precision as compared to traditional simulation tools. Simulation models were then developed with virtual sensors inbuilt in the motor. These virtual sensors generated data that was compared with the data from sensors on non-moving components.

5.3.3. Benefits

This work is useful for large electric drives where the temperature inside the motor in operation can reach up to 1000 degrees Celsius, creating a risk for

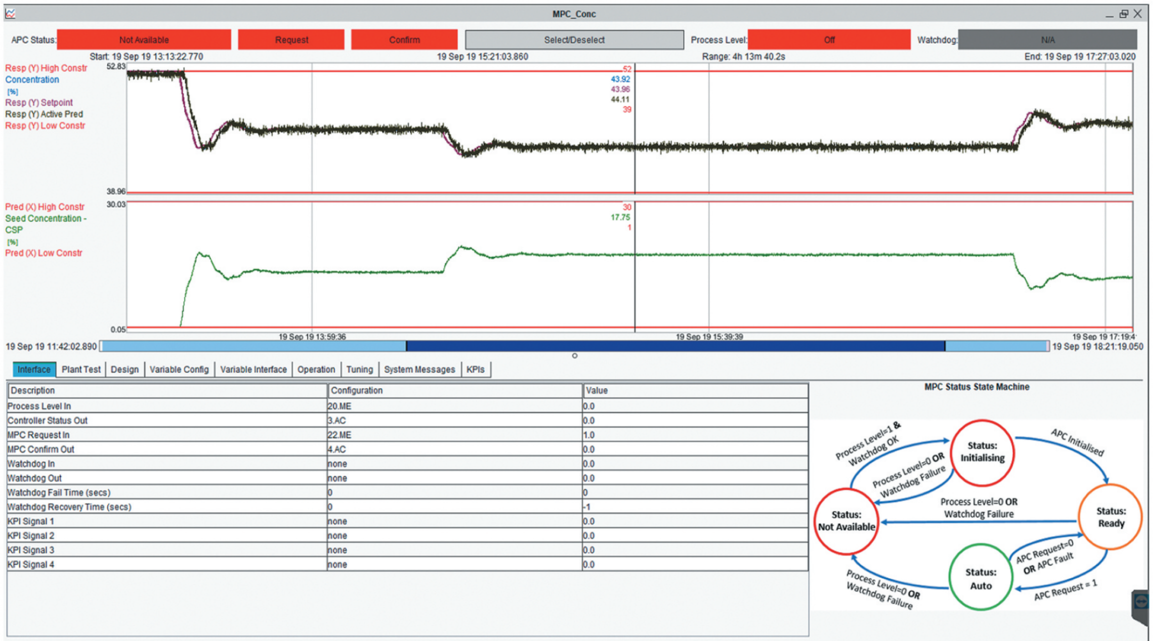


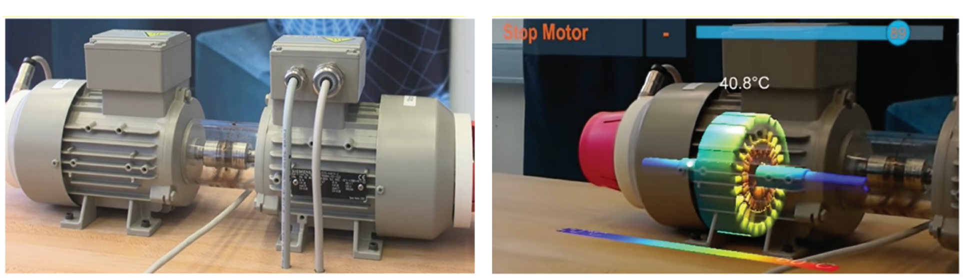
Figure 16. MPC Controller testing using the simulator environment and Process analytical tool (PAT) connected to soft sensors used for measuring key attributes not accessible to physical sensors.

deformation of material inside. The manufacturing process of electric machines is reliant on strict tolerances that have decisive influences on the operating behaviour of the machine. Therefore, to improve or better control the manufacturing processes for electrical machines, few attempts have been made towards the development of digital twin in EM manufacture. One example is current research by the Advanced Manufacturing Research Centre (AMRC) in Sheffield towards the development of a digital twin of an automated winding process for an electric motor (FEMM Hub Annual Report 2021). Another work by Weigelt et al. (2019), which has demonstrated the digital twin of the linear winding process based on the explicit finite element method, for the optimization of rolling processes.

6. Technical limitations and solutions

The research identified some technical limitations hampering the implementation of the current vision of digital twin in achieving closed-loop synchronisation between the digital and physical space/cyber-physical fusion (Qi et al. 2018; Tao et al. 2019). These technical limitations and proposed solutions are described in detail below:

Lack of quantifiable metrics of uncertainty in digital twin models, and unresolved uncertainties in the prediction of complex systems (Schuh and Blum 2016; Jones et al. 2020): Uncertainties are unique to systems due to the variability in the conditions that creates them. No two products from the same production line are identical in



(a) Stepper motor (b) Digital twin

Figure 17. Virtual X-ray of electric motors. From: (Bernard and Sandra 2018)

performance. The use of data-driven models is presented here as a solution to this challenge. The availability of microchips, digital tags and sensor technologies like the RFID technology has expanded data generation beyond geometrical measurements (Zhou et al. 2019). This has made scanning easier and quicker with reliable tracking capabilities to communicate operational information (Brenner and Hummel 2017). Integrated product-process models can then be fed with real-time data relating to their operational status such as environmental conditions, system performance, product quality etc. (Zhang et al. 2019c). Such real-time instance data can help in identifying the pattern of change in the behaviour/characteristics of the system/product. The use of machine learning algorithms can be used to engineer unique patterns/metrics that can be used to maintain the health of the system.

(2) *Virtual confidence*: This poses to be a challenge due to the multi-complexity of manufacturing systems resulting in engineering estimation and presumptions. Data from the factory floor is compared with data from the virtual model to investigate the behaviour of a machine in operation against expected behaviour. The use of real-time data instances in the virtual platform increase virtual confidence (Grieves and Vickers 2016).

Engineering models are known to be a very effective representation of well-known processes. Data-driven models are stochastic and tend to represent the variability of a system. This would be an effective means of representing the product-process interaction and the progressive development of the product. The management of virtual models and connectivity to the physical twin would be improved if they are built to the lowest possible level of granularity with unique identification, functionalities and control. The combination of both model approaches would increase the functionality of the integrated digital twin.

More research should be done to establish the benefits of using various virtual model approaches either separately or combined in the digital twin. It is interesting to know what levels of engineering and data models combination can be achieved. Trade-off analysis in use cases would highlight the advantages/limitations this combination presents.

(3) *Variance in the framework of the digital tools used to achieve virtual confidence, i.e. linking models with data from the factory floor (machine or sensor data)*: One major challenge with the digital tool used to achieve virtual confidence lies in the variance of the functional/data semantics/communication frameworks (Tao, Zhang, and Nee 2019). Interaction/access to heterogeneous digital platforms/data sources is limited because they are dependent on the integration endpoints and the capabilities of the database they are built to work on. This has limited the integration of tools from different vendors needed in implementing cyber-physical integration that supports real-time communication for smart production (Blum and Schuh 2017; Zhang, Tao and Zhang 2017; Cheng et al. 2018).

A potential solution is for middleware vendors to encourage software collaborations by adopting widely accepted communication protocols. An example includes the collaboration between MTConnect and OPC_UA communities to provide an MTConnect-OPC_UA specification that improves the interoperability and consistency between both standards. This capacity is transferable to all manufacturing technologies, equipment, devices or software implementing these standards. The integrated process-product digital twin as an aggregate model requires more collaboration between machines/equipment and virtual entities. Communication constraints associated with using heterogenous digital platforms in building the models can be handled by either using the same digital platform or using platforms with unified data/communication semantics that supports real-time communication like the OPC-UA/MTConnect.

Another potential solution is the standardisation of information model semantics. The systematic approach towards the development of semantics for information models would encourage a continuous effort towards the conformance and usage of the same standards

(Zhang, Xu et al. 2019). This would allow modelling platforms to effectively represent both the product and process composition. For example, the ISO 10303 standard provides a neutral data structure enabling CAD systems to exchange product data. ISO 14649 and ISO 10303–238 standards uses modern associative language enabling direct connection between CAD design data for machining and downstream fabrication processes (Lu, Xu, and Wang 2020).

Software vendors in collaboration with researchers should expand the capabilities of their products. Newer versions of existing digital twinning software with collaborative capabilities that supports the combined representation of process flow and product behaviour is needed. The idea of a closed-loop integrated digital twin that recreates the product-process interaction using enhanced 3D visualisation and data would be an added advantage for more investigative results in diagnostic analysis.

(4) *Lack of an explicitly defined ontology*: A closed-loop supply chain network would need an explicitly defined ontology. Providing an overt formal specification of the network conceptualisation and standards enables seamless business integration between trading partners (Lu et al. 2020). Ontologies have an essential role to play to ensure adequate flow of information, reuse of data between project phases, easy information accessibility, integration of process and product models with enterprise resource planning (ERP) systems, data communication through the network and reading data stored in electronic tags and databases (Cai et al. 2017; Negri et al. 2019). Blum and Schuh (2017) discussed several ontologies for IT systems that use RFID technology to achieve the smart linkage between the virtual and physical world.

(5) *Challenges in the inclusion of human functionality in the virtual space*: Cyber-physical integration in manufacturing also involves the inclusion of human functionality resulting in more human-machine interactions. The old control methods involve more human control which limits the autonomy of the system and restrict human-machine collaborations. Another challenge here involves the difficulty in transferring human operations into machine procedures to be handled by the machine to increase precision and performance.

Digital twinning promotes human-machine collaborations where precision is managed by the machine and certain decisions are handled by the operator. More effective and fast communication links are needed to ensure such interactions are seamless and aligned to the system operation. Also, designed algorithms should adopt object-oriented structures in ways that allow human inputs as part of their operational blocks. State-of-the-art technologies for human-machine interface includes augmented and virtual reality, natural voice processing and gesture control. The concept of immersion stands to be an effective approach for virtual human-machine interaction.

Voice interaction is the most effective and quickest means of expression for human beings (Nagabushanam, George, and Radha 2020). Nagabushanam, George, and Radha (2020), highlights advancements in Natural language processing (NLP) using neural networked-based methods. This has been applied in deep learning (DL) and long short-term memory (LSTM) algorithms with a certain level of accuracy and efficiency. In recent times, advancement in remote sensing technologies has contributed to better gesture recognition. Technologies like ambient light, cameras and image processing, sound and wearable devices, Radiofrequency (RF) and mmWave radar are been used to capture operator activities. With faster communication, sensing and processing capabilities, the development of gesture training and control is a promising development for the digital twin system.

(6) *Lack of professional skills sets*: The fourth industrial revolution comes with a wave of new technologies demanding new skill sets to manage them. To create more ways for the actualisation of the digital twin concept, the manufacturing industry continuously needs to liaise with academia to make fast advancements towards these emerging technologies, contextual and social resources (Ward et al. 2021). The industry

provides the funding, expertise, application knowledge and related field data. Academia provides the technological know-how like advanced methodologies from mathematics, control and computer engineering and takes responsibility for grooming the new generation workforce equipped with interdisciplinary skills. These will result in a progressive transformation of their industrial/research environment, and work method. A collaboration between these two sectors creates a versatile learning environment with a bidirectional channel for knowledge sharing and transfer resulting in the combination of theoretical knowledge with industrial practices.

(7) *Challenges in managing big data, defining semantic data models, data management systems and scalable databases for data storage on a single platform, the integration of existing simulation packages and semantic interoperability of data from heterogeneous sources*: Data models mostly used in engineering and simulation tools are not compatible, resulting in data silos within production systems (Macchi et al. 2018). There is the issue of insufficient details to meet all parameter needs. Also, the proprietary format limits the amalgamation of relevant engineering data and models for each object. The heterogeneity of gathered data from both physical and virtual spheres poses to be a challenge. The proposed DT framework supports an extensible framework for data acquisition (data gathering, storage, organisation and distribution) and analyses for all parts of the system. Lu and Xu (2018) presents semantic web technology, an evolution of the World Wide Web technology as a distributed and scalable standardised interface for the surrounding systems. This creates a graph of connected facts by linking up documents to pieces of information. The actualisation of uniform data interfaces and out-of-step data computing technologies is also a potential solution to these challenges.

7. Conclusion

This paper presents a literature analysis on the digital twin concept to address the question: *'How does the digital twin concept support the realisation of an integrated, flexible and collaborative manufacturing environment as one of the goals projected by the fourth industrial revolution?'*. A review of the literature was conducted to investigate the development of the digital twin concept, maturity and its vital role within the manufacturing industry. Six key functionalities inherent in the digital twin applications were identified: prognostic and diagnostic analyses, simulation (online and offline), control, monitoring/supervision and optimisation. The review findings also highlighted that there was no common framework for a digital twin model creation. This study proposed a conceptual framework that enables the integration of both product and process digital twin and the evolution of digital twin data. The application, methodology and benefits of the proposed framework were illustrated in two case studies. The case studies demonstrated that within manufacturing, the digital twin serves as a medium for achieving cyber-physical integration through bidirectional interaction, data analytics and linking of information silos all through the product cycle. The proposed framework allows automated configuration of production setups using the virtual product specifications. Finally, technical limitations and proposed solutions for the implementation of the digital twin concept in manufacturing were discussed.

The digital twin concept is still evolving. More research on digital twin modelling framework, digital twin modelling tools and applicative demonstrations from different fields using integrated product-process digital twin would prove its diversified usefulness, highlight more business benefits, encourage more investment and further adoption in existing industrial infrastructures. The idea of controlling physical assets from virtual models presents more research opportunities.

Acknowledgments

The authors acknowledge the support of Airbus and the Royal Academy of Engineering under the Research Chairs and Senior Research Fellowships scheme (RCSRF1718\5\41).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the Engineering and Physical Sciences Research Council of the UK through the Future Electrical Machines Manufacturing Hub (EP/S018034/1) and the Made Smarter Innovation -Research Centre for Connected

Factories (EP/V062123/1). The work was also supported by the Petroleum Technology Development Fund (PTDF) of the Federal Republic of Nigeria (PTDF/ED/PHD/OIU/1292/17).T

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