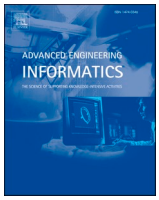
Advanced Engineering Informatics 62 (2024) 102567



Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei



Full length article



A unified framework for digital twin development in manufacturing

Christina Latsou [a,*], Dedy Ariansyah [a], Louis Salome [b], John Ahmet Erkoyuncu [a], Jim Sibson [c], John Dunville [d]

[a] Centre for Digital Engineering and Manufacturing, Cranfield University, Cranfield MK43 0AL, United Kingdom
[b] The Boost Society, Paris 92300, France
[c] Babcock International Group, Bristol Business Park, Stoke Gifford, Bristol BS16 1EJ, United Kingdom
[d] Babcock International, Devonport, Plymouth PL1 4SG, United Kingdom

ARTICLE INFO

Keywords:
Digital twins
Digital Twin development framework
Ontology
Manufacturing

ABSTRACT

The concept of digital twin (DT) is undergoing rapid transformation and attracting increased attention across industries. It is recognised as an innovative technology offering real-time monitoring, simulation, optimisation, accurate forecasting and bi-directional feedback between physical and digital objects. Despite extensive academic and industrial research, DT has not yet been properly understood and implemented by many industries, due to challenges identified during its development. Existing literature shows that there is a lack of a unified framework to build DT, a lack of standardisation in the development, and challenges related to coherent goals of DT in a multi-disciplinary team engaged in the design, development and implementation of DT to a larger scale system. To address these challenges, this study introduces a unified framework for DT development, emphasising reusability and scalability. The framework harmonises existing DT frameworks by unifying concepts and process development. It facilitates the integration of heterogeneous data types and ensures a continuous flow of information among data sources, simulation models and visualisation platforms. Scalability is achieved through ontology implementation, while employing an agent-based approach, it monitors physical asset performance, automatically detects faults, checks repair status and offers operators feedback on asset demand, availability and health conditions. The effectiveness of the proposed DT framework is validated through its application to a real-world case study involving five interconnected air compressors located at the Connected Facility at Devonport Royal Dockyard, UK. The DT automatically and remotely monitors the performance and health status of compressors, providing guidance to humans on fault repair. This guidance dynamically adapts based on feedback from the DT. Analyses of the results demonstrate that the proposed DT increases the facility's operation availability and enhances decision-making by promptly and accurately detecting faults.

1. Introduction

The concept of Digital Twin (DT) has gained significant attention in both academic research and manufacturing industry. Since 2018, there has been a noticeable increase in scientific literature focusing on the development of DTs for manufacturing systems and processes [1]. However, despite the rapid growth, many articles argue that the concept of DT is still evolving and a considerable number of DT implementations still fall short of meeting the requirements of a genuine DT [2,3]. In this regard, Kritzinger et al. [4] emphasised the need for a clear distinction between DTs, Digital Models and Digital Shadows, as depicted in Fig. 1 (adapted from [4]). According to these concepts, a DT should facilitate bi-directional communication between the physical object and its digital counterpart, enabling changes in one entity to be directly reflected in the other. However, the majority of use cases still fall into the category of Digital Shadows, due to the absence of bi-directional communication. Similarly, Cimino et al. in [5], in their review focusing on the automation pyramid, argued that a significant number of DT applications in the literature lacked the required connection to the control system of their physical counterparts, thereby limiting their ability to provide the services outlined by [6]. Jones et al. in [7] raised the question of why many DT applications do not incorporate a virtual-to-physical connection, despite its inclusion in Grieves' original definition. Furthermore, Fuller et al. in [8] claimed that the lack of a precise definition of DT has led to misconceptions in its development. To address these concerns and provide further clarity on the notion of DT, several scholars have revisited

* Corresponding author.
E-mail address: Christina.Latsou@cranfield.ac.uk (C. Latsou).

https://doi.org/10.1016/j.aei.2024.102567
Received 1 February 2024; Received in revised form 18 April 2024; Accepted 22 April 2024
Available online 4 May 2024
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the original concept and clarified the distinction between DT and other similar concepts such as Digital Models and Digital Shadows [1,3,4,8]. Despite these efforts to differentiate among 'Model', 'Shadow' and 'Twin', ambiguity still, exist, particularly in the context of smart manufacturing. Further research and clarification are needed to ensure a common understanding of the DT concept and its proper implementation in various domains.

Moreover, efforts have been made to propose guidelines for the development of DTs in manufacturing. These guidelines aim to provide a structured approach and framework for building DTs. Towards this effort, Jones et al. [7] consolidated 13 characteristics of DT along with a DT framework and its operation. From the reviewed papers, all DT elements, concepts and the meaning of these characteristics are given and mapped into a framework. However, the description of these concepts remains abstract, lacking detailed implementation guidance on how to construct a DT. Similarly, while Barricelli et al. [9] identified specific characteristics that a DT should possess based on existing DT applications, they lacked insights into their implementation and integration. To ensure that future DT development aligns with the conceptual definition proposed by Grieves [10] and addresses the call for clarification from scholars, it is essential to move beyond conceptualisation. There is a need for a clear development guideline and unified framework that not only defines the components of a DT but also provides an implementation path for consistent conception, standardisation, establishment and management.

Although several DT frameworks exist in the literature, scholars have identified a lack of a unified generic framework with standardisation in the DT development and the need to align goals for multi-disciplinary teams involved in designing, developing and scaling DT systems [3,8,11]. This research paper proposes a unified framework for DT development that provides a detailed step-by-step implementation path. The key contribution of this framework lies in harmonising existing DT development frameworks, unifying concepts, and process development. To demonstrate the practical application of the proposed framework, this paper presents a real-industrial case study of DT development.

The remainder of the paper is structured as follows: Section 2 reviews existing DT frameworks, discussing its characteristics and limitations, and identifying research gaps in the field. Section 3 presents the approach to unify existing frameworks, proposing a comprehensive and standardised unified framework for DT development. Section 4 presents a real case study, conducted in collaboration with Babcock International, demonstrating the application of the proposed framework in DT development. Section 5 discusses the results obtained from implementing the unified DT framework, along with feedback received from the industrial partner. Section 6 concludes the research work and proposes future research direction.

2. Literature review

2.1. Digital twin framework development in manufacturing

In this study, a comprehensive review methodology was employed to explore the existing literature on the development of structured approaches for DTs in the manufacturing industry. The search was conducted using the Scopus research repository. The keywords used to retrieve the relevant documents were: (i) "Digital Twin development framework" OR "Digital Twin framework" OR "Digital Twin architecture" OR "Digital Twin reference model" OR "Digital Twin model" AND (ii) "manufacturing". The search was not restricted by a lower time limit and the search period extended up to December 2023. After retrieving the initial set of documents, a two-step filtering process was applied. Firstly, duplicate documents were removed to ensure only unique publications were included. Secondly, the selection was narrowed down to documents written in English, excluding all the healthcare and social science studies. Additionally, the reference lists of the identified documents were examined to identify any additional relevant studies that were not captured in the initial search. The same criteria for inclusion and exclusion were applied to these documents. This iteration produced a total of 58 documents to be considered for review in this study. It is noted that this work does not constitute a systematic literature review on DTs. For a more comprehensive exploration of the current state-of-the-art, opportunities and challenges in the field of DTs can be found in [3,8,12–19].

Considering the existing literature on DTs, there has been a growing interest on the development and application of DTs in the context of manufacturing. As a result, several frameworks, methods, architectures and reference models have been proposed to provide guidance in this domain. These studies aim to offer a generic methodology for the design, integration and operation of DTs within industrial systems. In particular, research works have focused on defining the architectural components and interfaces of DTs in manufacturing [20]. This involves determining data flow, establishing communication protocols and integrating with other systems [11,21–29]. Another area of focus in research has explored the functional capabilities and design elements of DTs in manufacturing processes, including real-time monitoring, predictive analytics, anomaly detection, optimisation and simulation [30–39]. Additionally, data integration and management have been recognised as crucial aspects for DTs. In this regard, effective methodologies for data collection, fusion and storage to ensure accurate and timely data availability have been proposed [21,40–47].

In line with these studies, the approaches for structured DT development have gradually evolved to address the inherent complexity and uncertainty of manufacturing systems. Grieves in [10] made a significant contribution by introducing a standard DT architecture comprising three dimensions: the physical entity, virtual model and connection. The

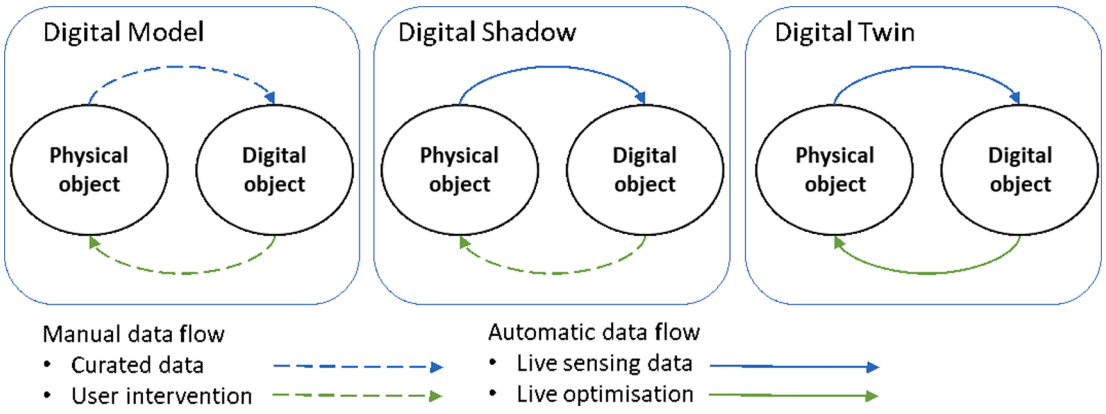


Fig. 1. Classification of Digital Model, Digital Shadow and Digital Twin based on data flow integration.

virtual model consists of sub-models in four dimensions: geometric, physical, behavioural and rule based models, each with their characteristics and functions. These sub-models can be assembled or fused to achieve the virtual mapping of the DT for the physical entity. Expanding on Grieves' work, Tao et al. [32] proposed a more comprehensive five-dimensional DT model for complex equipment, incorporating two additional dimensions, namely DT data and services. According to Tao et al. [48], out of 63 publications on DTs in the context of manufacturing, 29 of them successfully incorporated all four dimensions, indicating a balanced research focus across these dimensions. In 2022, Jia et al. [49] presented a theoretical modelling method, proposing the decomposition of complex DTs into simpler models within a 4C architecture, based on composition, context, component and code. These models are then assembled using information fusion, multi-scale association and multi-context interaction. This method enables the simulation of multi-scale, multi-dimensional and multi-scenario environments within complex DTs. Furthermore, Latsou et al. [50] introduced a DT integrated into a Cyber Physical System (CPS) architecture for improving the resilience of complex manufacturing systems. Inspired by Lee et al. [51], this work extended the 5C CPS architecture, using a multi-agent approach, was implemented to allow DT integration. The agent-based modelling approach that offers modularity, flexibility and interactivity [52,53] was employed to automatically detect anomalies, identify and remove bottlenecks.

Moreover, the concept of proactive, active and autonomously adaptive DTs in shop floors has attracted significant interest. Stark et al. [38] proposed an eight-dimensional model to define the scope and objectives of a DT solution for a smart factory. While it effectively captures the different dimensions of a DT solution and their interdependencies, further refinement is needed to address cross-dimension dependencies and provide more explicit step-by-step design reasoning. From this model, six DT design elements for DT development and their influence factors were identified. These DT design elements are categorised to inform the linkages between the physical system components, the related software controlled system and the data-driven analytic design elements. Furthermore, Erkoyuncu et al. [23] introduced a design framework for adaptive DTs in the context of manufacturing. The framework aspires to address the challenges posed by evolving and changing manufacturing systems by enabling DTs to adapt and evolve concurrently with the physical systems they represent. The framework is structured into four stages: requirement analysis, model development and calibration, adaptive decision-making and continuous improvement. Additionally, Yang et al. [41] presented a model-driven DT architecture for shop floors using a *meta*-model-based approach based on RAMI 4.0. The proposed architecture consists of three implementation elements: *meta*-model construction, data modelling (including data interaction between cyber-physical spaces) and the creation of integration-level models for the shop-floor DT through iterative feedback between requirements and models. The DT architecture enables real-time monitoring, simulation and optimisation of shop-floor operations. The aforementioned studies can, therefore, contribute to the advancement of adaptive DTs in manufacturing by providing frameworks, architectures and proactive approaches to optimise processes, detect anomalies and improve decision-making on the shop floor. Despite the identification of key elements necessary for DT development in existing approaches, a notable gap exists in the form of a comprehensive and systematic framework that provides a clear, step-by-step process. What is currently lacking is a framework that offers flexibility and presents multiple options to be considered based on the unique characteristics and suitability of each case study. The goal is to provide guidelines for DT development that are adaptable and can accommodate diverse scenarios, rather than offering a singular solution that cannot be easily generalised. This emphasis on flexibility and adaptability is crucial for effectively implementing DTs in various industries and contexts.

In addition to these approaches, the adoption of standardised reference architectures is gaining importance in engineering DTs. The ISO 23247 standard [54] offers a reference architecture for DTs in manufacturing. This architecture consists of an entity-based reference model and a functional view that describes the functional entities that have influenced the research conducted in this study. However, Ferko et al. [55] highlighted a misalignment between existing DT architectures and the ISO 23247 reference architecture, indicating that the adoption of the standard is still in its early stages. Existing DT architectures in manufacturing primarily focus on functional aspects while neglecting non-functional entities and recommended functional entities outlined in the ISO 23247 standard. Additionally, the reference architecture lacks support for key elements such as data storage and DT versioning, which are present in current architectures [15]. Aligning with the ISO 23247 reference architecture is important for addressing challenges related to interoperability (i.e. effective exchange and use of information between different systems) and evolvability (i.e. the ability to adapt and accommodate changes over time) [11]. To address these challenges, future work includes refining the reference architecture, assessing systems interoperability and expanding functional entities to incorporate implementation details and new functionalities. While aligning with ISO 23247 is valuable, continuous evolution of the standard is necessary to address implementation details and incorporate emerging features.

2.2. Research gaps

Based on current literature on DT framework development in manufacturing, further investigation and advancements are necessary in several areas to establish a unified framework. In this regard, a detailed methodology and standardisation are needed to address the absence of a common framework, facilitating the creation of DTs and ensuring interoperability among different implementations [15,41,55,56]. Additionally, challenges related to data collection, storage, integration and synchronisation from diverse sources require the implementation of efficient techniques and systems to ensure accuracy and consistency in the development of DTs [2,14,43]. Modelling complex manufacturing systems and understanding, simulating and controlling real-time changes present further challenges that can be addressed through the development of high-fidelity models and simulation techniques [35,37,42,57]. Furthermore, scalability and performance issues in large-scale DT systems that generate massive volumes of data require the development of efficient data storage, processing and visualisation techniques to enable real-time capabilities [58,59].

The DT implementation in manufacturing faces additional challenges, including the need to ensure data security and privacy through the development of secure architectures, encryption techniques, access control mechanisms and privacy-preserving algorithms [17,60]. Moreover, the successful implementation of DT technology can be hindered by a lack of awareness and resistance from companies. Overcoming cultural barriers, promoting data sharing and investing in software and services can, thus, help with the adoption of DTs [15,16,60]. Additionally, optimising the interaction between humans and DTs is crucial for effective collaboration and decision making, which can be achieved through the development of intuitive user interfaces, visualisations and interaction techniques.

Addressing these research gaps will contribute to the development of a comprehensive framework for developing DTs in manufacturing. This, in turn, will foster widespread adoption and the successful implementation of DTs, leading to improved efficiency and informed decision making. Thus, this work aims to propose a comprehensive and unified framework for the development of DT in manufacturing. This proposal hinges on the strategic deployment of efficient techniques encompassing data collection, storage, integration, model development, data visualisation, and data exchange. At its core, the framework is designed to facilitate seamless bi-directional communication between physical and virtual assets, thereby systematically advancing the development of DTs in manufacturing.

3. A generic unified DT development framework

DT development can vary widely from one application to another in terms of the object being represented, underlying data and models, as well as the lifecycle stage considered. Nevertheless, every DT application is composed of building blocks, including data and models, data analysis, user interface and communication network where different underlying technologies of DT can be categorised into. The arrangement of these building blocks makes it possible to produce a framework that systematically guides the development of the DT, irrespective of the use cases. This guideline encompasses the initial planning phase for the organisation's DT purpose, the identification of essential DT design elements, and the verification process. It guides the development trajectory through to the validation phase, ensuring the confirmation of the DT's successful realisation of its intended purpose.

This work proposes a generic and unified step-by-step framework to develop a DT. These steps, presented in Fig. 2, are discussed in Sections 3.1 - 3.7. The flow of the steps in the framework is guided by the conceptual definition of a DT, addressing identified challenges and ensuring a systematic progression from initial planning through requirements gathering to steps including data collection, model development, integration, validation and ongoing monitoring. This systematic approach offers flexibility and adaptability to different case studies, providing comprehensive guidance for DT development across various industries.

3.1. Step 1: Defining the DT requirements

DT is a complex approach to develop, which involves the integration of multiple technologies, system of systems and computation methods. Having a clear understanding of what significant benefits the DT will bring to the current operational performance is crucial during process planning. Otherwise, the expected benefits will not be realised, leading potentially to the devaluation of DT. To maximise the impact of DT, the initial development step involves defining its purpose and scope. The focal point of consideration is to rationalise the necessity of the DT by addressing Q1: '*What is the function of the DT*?' and '*What expected improvements are anticipated compared to the current operational performance*?'.

For an organisation, the hierarchical level of the DT system can be categorised into: (i) enterprise level that refers to the whole business system such as product or service offering, supply chain, integrated business chain, etc.; (ii) factory level that refers to the production process and capabilities; and (iii) equipment level, which refers to the functionalities and state of physical value generated asset [61]. Following this hierarchy, a common approach is to begin at lower levels and progressively scale up. However, regardless of the hierarchical level, every DT initiative should address the fundamental questions in terms of purpose and scope. Additionally, each level may have multiple DTs exchanging information in which every single DT may consist of multiple DT modules that perform specific functions (e.g. monitoring performance, detecting disruptions, etc.). The decomposition of a DT into modules facilitates the control and management of interdependence and independence of the system when building and scaling up the DT. This can also ensure reusability, extensibility and maintainability when changes or system errors are encountered. The hierarchical levels of interconnected DT systems in manufacturing are presented in Fig. 3.

The question to address is Q2: '*What interface does the DT have, considering other DTs or DT modules?*'. The interconnection of DTs implies a need to define the interface(s) and data sharing between DTs. The increasing level of integration, both horizontally and vertically, entails more useful insights to be obtained, but also induces a growing challenge related to analytics capabilities and data sharing. The increasing number of horizontal integrations requires an incremental effort to extract meaningful information. The synthesis and analysis of vertical integrations increase the complexity even more due to more complicated data sharing and ownership policy.

3.2. Step 2: Determining the DT data and models

DT relies on data and models to generate insights, enable productive control and co-evolve with its physical counterpart. Data and models are identified in this step to enable digital representation by capturing the current status and behaviour of the physical system or process, a concept referred to as physical-to-virtual mapping [3,7]. Based on the DT purpose and expected performance improvements, defined in the first step, the required data and models for the DT are identified. This requirement mapping ensures that the collected and generated data are indeed useful and usable for improvement purposes, avoiding overcomplicating or overengineering DT.

The key aspects in defining DT data are the types of data needed to be mapped with the requirement of DT modules, data interface(s) and data constraints. Hence, for each DT module, the question to address is Q3: '*What types of data, data interfaces and data constraints need to be considered?*'. The data types depend on the asset[1]'s lifecycle being considered. As the DT moves from the equipment to the factory level, multiple stages of the asset's lifecycle are involved, capturing the entire lifecycle when the enterprise level is considered. In each stage of an asset's lifecycle, different types of data can contribute to DT development [62], including:

- System specification data: static data that representing the technical specifications of the asset being twinned, sourced from user manuals, technical datasheets, etc.
- Sensor data: output from devices detecting and responding to inputs from the physical asset. This data captures changes in the asset's shape, operation, and environment.
- Control and actuator data: indicates the state or status of controls and actuators governing the physical asset.
- Network data: pertains to network performance and data flow across different sub-systems, encompassing details such as data size and transfer speed.
- Software data: generated from other software systems, including Product Lifecycle Management (PLM), Enterprise Resources Planning (ERP), or other DT systems.
- Database data: typically historical data recorded in the past, covering resource utilisation, maintenance duration, frequency and others.
- User data: collected from human input to track the operation and actions performed on the physical asset, either through the human–machine interface or the internet.
- Human-machine interaction data: collected to adjust the working parameter of a physical asset to better align with human capabilities. This may include physiological data, eye-tracking data, etc.
- Human data: collected specifically from individuals interacting with the physical asset or providing input through the human–machine interface or the internet. This influences the operation and optimisation of the physical asset and may include user feedback, preferences, biometric data, survey responses and user-generated content.

After identifying the data types required for the DT development, the models to represent the static and dynamic conditions of their physical counterpart should be identified. Tao et al. in [6] proposed that virtual models for a DT product can involve geometrical, physical, behavioural, and rule modelling. For larger scale DTs involving multiple business processes, integrated simulation methods, including system dynamics, agent-based modelling and discrete-event simulation, are proposed to model the production enterprise [63]. In the context of cyber-physical manufacturing systems for people, where human plays a significant role, a DT for understanding the human state in the workforce is required to monitor, for instance, their well-being and maintain safe

[1] It is noted that in this work, asset may represent a product, system or process in the context of manufacturing industry.

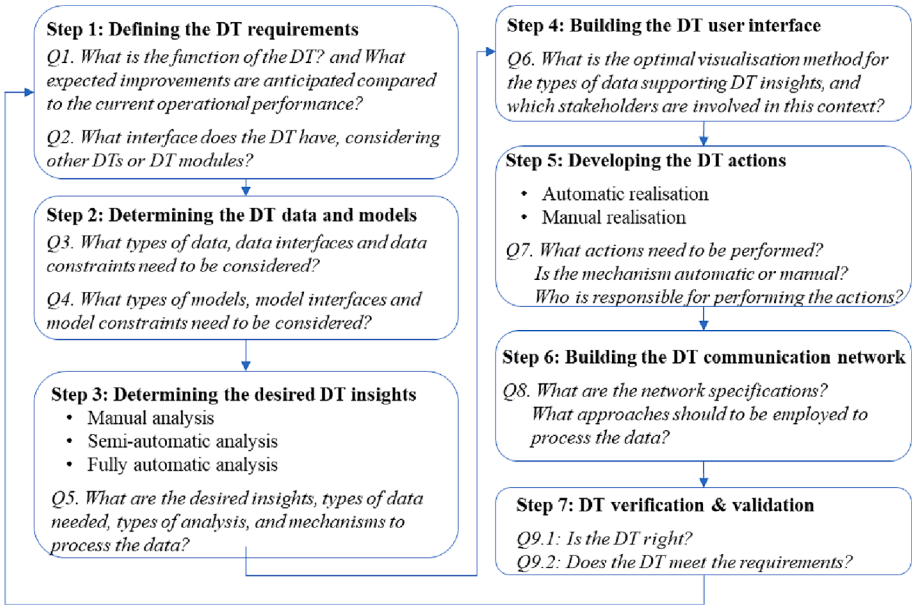


Fig. 2. A unified step-by-step framework for DT development.

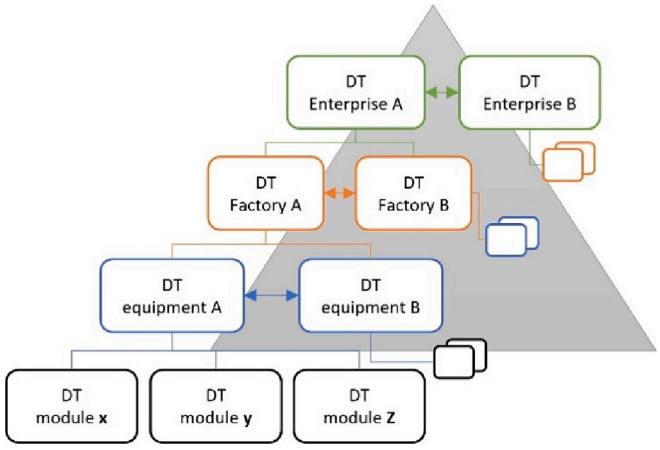


Fig. 3. Hierarchical levels of interconnected DT systems in manufacturing.

working condition [2]. The DT development for people will require the development of a human behavioural model [64], a human intention model [65], workload and attention and additional human characteristics such as skills and preferences [66]. A virtual model can allow not only a better understanding of how the physical system operates and behaves, but also enables the analysis of underlying causes behind the behaviour of the system, estimate future conditions and allows performance to be measured in several scenarios. The key aspects in defining a DT virtual model are the types of models needed to be mapped with the requirement of DT modules, model interface(s) and model constraints. Thus, for each DT module, the question to address is Q4: '*What types of models, model interfaces and model constraints need to be considered?*'.

Data acquired from diverse sources may exhibit disparities in terms of format, dimension, update rate or structure. Frequently, this data is fragmented and stored in disparate systems with multiple access interfaces. Consequently, the integration or direct processing of data from one system or model to another proves challenging unless the data adheres to a standardised format that enables system interoperability, exemplified by ISO 13399, as evidenced in CAD/CAM/CNC integration [2]. The structuring of data in a standardised format can bridge the gaps in data exchange within DTs. However, the standardisation of an information model for DTs, elucidating data structure and semantics, currently faces limitations in accommodating various types of data models [2,16]. In situations where a standard is yet to be established, the acquisition and processing of data from heterogeneous sources can impede the establishment and enhancement of DTs.

In this regard, the OPC Unified Architecture (OPC UA) serves as an open standard for facilitating data exchange across diverse devices in factory automation, evolving into a universal data standard for industrial automation. However, while OPC UA provides a robust information model complemented by extensible references, the existing vocabularies within OPC UA alone fall short of delivering comprehensive reasoning capabilities. Efforts are underway to incorporate semantic support [67], an essential feature for connecting and comprehending information across various systems, thereby playing a pivotal role in advancing the evolution of DTs [23]. Furthermore, this advancement can potentially result in the establishment of a universal file format and standardised interfaces catering to different systems, facilitating seamless access, storage, and updating of various information types. This realisation is achievable through the application of ontologies, a well-established approach in the formalisation and comprehension of data in heterogeneous distributed systems. Ontologies enable the creation of shared semantic vocabularies, structuring and contextualising diverse data in a manner understandable among various systems, eliminating the need for proprietary formats [68]. Moreover, prior to the integration, storage, and utilisation of DT data, it is imperative to identify data constraints, taking into account the heterogeneity of data sources. This step is crucial, as data originating from diverse sources may exhibit variations in terms of readiness, accuracy, precision, consistency, completeness and validity, necessitating data transformation processes.

3.3. Step 3: Determining the desired DT insights

The integration of data and model, as discussed in Step 2, should enable actionable insights to be derived and used for improving the control and decision making of assets [3,69]. Unlike the traditional siloed system, DT paves a way for the integrated analysis that comes from simultaneous data processing and data aggregation to generate useful insights that can be used to achieve the expected improvements defined in Step 1. There are three different ways to carry out analysis with DT, considering the human and asset performance consequences [70], as: (i) manual analysis; (ii) semi-automatic analysis; and (iii) fully automatic analysis. Both manual and semi-automatic analysis require

human intervention to update the DT in terms of incorporating new information or instructions to reflect the change in the physical asset or to improve the current information resources to steer the management and handling of the physical asset. Considering the desired insights, one should identify and consider the types of data needed as defined in Step 2, the type of analysis and the medium or tool/software to process the data. The question to address is Q5: '*What are the desired insights, types of data needed, types of analysis, and mechanisms to process the data?*'.

3.3.1. Manual analysis

The manual analysis involves human knowledge to derive critical information from the DT. In this analysis mode, the role of the DT is to provide the basic information required for the user to support their task. A common example is the visualisation of the current state of the system or several parameters of interest allowing monitoring and controlling the asset's performance. This may include the visualisation of machine states and energy consumption [5], the visualisation of abnormal states in the production process [47], the visualisation of robot capability to assist programming and safety system assessment [71] or visualisation of fault information to support corrective maintenance [72]. This type of analysis requires the user to interpret the presented information and further elaborate it to realise improvements in the physical system. Thus, users are responsible for decision making and accordingly updating the DT.

3.3.2. Semi-automatic analysis

The semi-automatic analysis involves the use of algorithms and simulation models to enable users to run 'what-if' scenarios to support decision making. The role of DT is to allow users to enhance the capabilities of assets by offering optimised solutions. The process of optimisation can be performed by defining boundary conditions or changing different parameters to identify the best asset configuration or opportunity for improvement. The typical examples include the optimisation of the production process according to the production plan [73], optimisation of energy consumption used by manufacturing resources [36], optimisation of warehouse management in reducing storage and picking cost [74] and verification of production process control effectiveness [75]. In this type of analysis, instead of manual analysis, DT extracts insights from a complex situation and acts as a decision support for the users to optimally operate the physical asset. A number of recommendations are provided to the users are presented with some suggestions of the decisions and then they need to choose and update the DT.

3.3.3. Fully automatic analysis

The fully automatic analysis involves the use of interconnected systems and services to generate automated planning or decision making. DT in this role is equipped with an intelligent capability to assess and update its state and learn relevant information from all available systems to prescribe a decision or a solution. Typical examples of this type of analysis are the automated generation of work plans which takes consideration of employee's characteristics to generate the optimal solution [66], automatic assembly planning exploiting semantic information of part connections in the product description [76], automated generation of collision-free robot control program [77]. This mode of analysis leaves the decision and the update of the DT to be controlled by itself, whereas the users receive the information to implement the decision.

3.4. Step 4: Building the DT user interface

DTs should provide an effective user interface to visualise information to the users and provide interaction to the DT and its physical counterpart. Considering that a DT collects, processes and aggregates heterogeneous information from multiple sources to realise valuable insights or services, managing the visualisation of various integrated information for the DT can be a challenge. DT visualisations are commonly presented in the form of 2D (e.g. dashboard) or 3D visualisation (e.g. Augmented Reality (AR), Virtual Reality (VR) or Mixed Reality (MR)). However, when and how to use the right form of visualisation is scarcely discussed in the literature. The goal of choosing and designing a suitable virtual representation is to ensure that the DT can provide an accurate view of the physical asset and convey meanings that are understood and utilised by the users.

Previous research has shown that while 2D and 3D can be used to understand the relationship of multiple information, they are effective for different tasks [78]. It has been argued that 2D visualisation enabled the establishment of accurate relationships between parameters, whereas 3D visualisations were useful to gain a qualitative understanding and visualising data [79]. In the context of DTs, 2D visualisation has been employed in the field of production, planning and control (PPC) where DTs support users in the creation of production plans [80] and maintenance work plans [81]. The users were enabled to analyse precise information integration with schematic diagrams, a series of plots or numbers and numeric tables. Meanwhile, 3D visualisations of DT using AR were shown to enhance suspicious anomalies detection in the field of maintenance where DT supports communication between facility manager and site worker to identify the problematic asset [82].

Additionally, it has been argued that 3D visualisation can be successfully employed for operational tasks that require collision detection such as when DTs are used to assess human-robot interaction [64] or teleoperation of the robot [83]. Moreover, 3D visualisations are often more appealing to the users than 2D, although this does not mean that 3D visualisations support user performance better than 2D views. Studies have proposed that 2D visualisations can be more useful in the visual search task [84] and precise spatial or relative position judgement [78,84]. These findings have suggested that the types of insights and tasks, for which a DT can provide support to the users, define the selection and design of the DT user interface. Therefore, in building the DT interface, one needs to define the mapping of insights and actions. For each type of insight and user task, the question to address is Q6: '*What is the optimal visualisation method for the types of data supporting DT insights, and which stakeholders are involved in this context?*.

The selection of visualisation methods (e.g. dashboard, VR, AR, MR, etc.), access authorisation, and level of detail may vary among stakeholders and depend on the specific insights delivered (refer to Step 3). For instance, a remote expert might require a 3D representation of the physical asset within an AR/VR environment to assess spatial relationships among components and assist a local operator in troubleshooting. However, visualising DT data for human users introduces critical considerations that, if overlooked, can compromise the advantages of DT. In this context, DTs aim to convey integrated information from diverse sources to humans. Neglecting human perceptual and cognitive abilities in information design poses a risk of users losing situational awareness of real-world events, potentially leading to human errors and accidents [85]. Additionally, DT facilitates automated data analysis to enhance decision-making in tasks performed by humans. Studies in human factors have revealed tendencies toward automation complacency and bias among humans [86]. When humans rely on decision-aiding automation that competes with their manual tasks, there is a tendency to forego sufficient checks, assuming that 'everything is okay.' However, if the DT is inaccurate, this assumption can lead to irreversible consequences. Considering these risks, associated with human reliance on automated decision-making, and the insights from human factors studies, the integration of AR with DT emerges as a strategic approach. By seamlessly incorporating relevant data into users' real-world environments, AR enhances human perception and interaction, promoting a symbiotic relationship between humans and automated systems. This approach can mitigate concerns of automation complacency and bias, allowing users to actively participate in decision-making processes while leveraging DT capabilities.

3.5. Step 5: Developing the DT actions

Developing actions involves deciding and implementing the DT insights obtained in Step 3. This includes updating the physical asset to synchronise with the virtual entity, ensuring the comprehensive realisation of the DT. The purpose of developing actions extends beyond the prevalent demonstration of virtual-to-physical mapping in DT research. It is crucial not only for maintaining synchronisation between physical and virtual assets but also for implementing improvements in the rectification, optimisation, and resilience of the physical asset based on insights gained from the virtual entity. For instance, when a change occurs in the physical asset requiring action to meet demand, the DT should detect and provide actionable insights to update itself. These updates are then actuated on the physical counterpart, either through control or productive feedback. While virtual-to-physical mapping is extensively discussed in DT research, the implementation of physical-to-virtual mapping is less emphasised, especially in manufacturing contexts [1,3–5]. Furthermore, although it is argued that the data flow from virtual-to-physical assets should be performed automatically to fulfil the DT concept [4], there may exist cases where the realisation of data exchange from virtual-to-physical is complex and thus requires manual intervention, as seen in maintenance scenarios [7]. The automatic and manual data exchange realisations are further discussed in Sections 3.5.1 and 3.5.2.

3.5.1. Automatic realisation

The type of virtual-to-physical data flow often relies on a controller (e.g. PLC) and actuator to execute the processed command from DT to the physical asset. Common examples in the literature include the execution of 3D printing operation from DT through the controller [87,88], the optimisation of the plant resources through the control of an automated guided vehicle (AGV) [89] and the control of industrial equipment such as boilers and generators [90]. Despite demonstrating the success of virtual-to-physical mapping, these examples were often tested in simplified environments or at a laboratory scale. In real scenarios, the operating situation is more dynamic and volatile, with numerous uncertainties. Consequently, process planning and adaptive control of the physical system can become significant challenges [85]. Automatic virtual-to-physical realisation faces challenges similar to those encountered in physical-to-virtual realisation in terms of sustaining twinning accuracy and resilience to disruptions. Existing literature has argued that physical-to-virtual mapping can be compromised by various factors, including missing data, temporary disruptions in the data feed, or models not updated due to the evolving asset [91]. To improve accuracy and resilience to disturbances, an intelligent agent-based approach was developed to detect and self-adapt, maintaining the consistency of virtual-to-physical mapping [91]. Similarly, a gap between the as-planned and the as-executed from DT to its physical counterpart is likely to occur. To address disruption and resilience issues, a smart agent should also be embedded in the actuator to manage disturbances. For example, the design methodology of smart actuator service for machine tools detects disturbances during program is running and adapts by making decisions according to defined goals and boundaries [92].

3.5.2. Manual realisation

For the realisation of virtual-to-physical connection, Jones in [7] argue that human involvement is still essential, especially in repair scenarios where DT is employed to assess the health of a component using predictive models. In such cases, a mechanic is dispatched to act based on the insights provided by the DT, facilitating the process of virtual-to-physical twinning. Instances of this manual realisation include leveraging DT for fault diagnosis [93] and improving the accuracy of Remaining Useful Life (RUL) predictions [94], followed by subsequent maintenance activities [32]. Beyond operational tasks like maintenance, [18] emphasised that manual realisation involving humans may extend to situations where individuals are responsible for control decisions while interacting with the DT. Examples encompass teleoperation of a robot [83,95,96] or implement instructions from DT, such as manual assembly task selection [38,77] and manual assembly task scheduling [66]. The automated realisation of virtual-to-physical connections is often challenging, particularly for complex tasks such as maintenance. In contexts that demand complex manipulation of the physical system, the concept of DTs as envisioned by some scholars might not be fully applicable at present.

When considering developing actions, it is essential to identify the necessary actions for each insight, determine whether the mechanism is automatic or manual, and specify who or what is responsible for performing the actions. Therefore, for each desired insight, the question to address is Q7: *'What actions need to be performed?'*, *'Is the mechanism automatic or manual?'*, and *'Who is responsible for performing the actions?'*.

3.6. Step 6: Building the DT communication network

A communication network is another key technology to establish a bidirectional synchronisation between DT and its physical counterpart to fulfil the DT concept: "*twinning of systems must occur between what existed in real space to what existed in virtual space and vice versa*" [97]. In order to ensure reliability and realise usability of the twinning process, the specifications of the communication network in DT are usually concerned with the establishment of real-time data communication [98], information latency [2] and cyber security [56,60].

Real-time data, or the twinning rate, refers to how frequently twinning occurs [7]. Many research works define a DT as a real-time digital representation of the physical asset that is the change in physical space is reflected in (near) real-time in the virtual space to enable either to act or respond simultaneously and equivalently to changes. Real-time data exchange capabilities facilitate a more responsive and adaptive process monitoring and operational optimisation. Examples that show the value of (near) real-time synchronisation are autonomy of part and fault handling [99], asset prognostic and health management [32], automated robot trajectory optimisation during human-robot collaboration [77], and process optimisation for dealing with geometrical product deviation during the production [100].

The specific requirement for achieving real-time synchronisation in the realisation of DT is often not explicitly stated. Instead, the term 'near real-time' is commonly used, implying a relative notion of real-time and suggesting a lack of precise definition for the level of synchronisation between the physical system and the DT. However, the term 'near real-time' does not provide a clear specification for the twinning rate. A more useful definition of real-time DT may be linked to the rate at which control process or decision-making needs to be made or realised from the DT, which can be categorised in terms of operational, tactical and strategic control. Operational control refers to the process whose state or data changes frequently in a short time (i.e. milliseconds to hours) and immediate handling needs to be made to control the process. For example, quality control in manufacturing often requires instant control to minimise defects in production. Tactical control refers to the change of state in which a decision needs to be made after a certain period (i.e. daily, weekly, monthly, etc.). For example, monitoring equipment reliability (e.g. MTBF) and maintenance management. Strategic control refers to the change of state in which a decision needs to be taken for a longer-term goal (e.g. 5–10 years). For example, opening a new facility or investing in a new product line.

In order to allow the information exchange to the physical asset, a communication link needs to be established and configured with the required data rate, latency and secured connection. These three network specifications depend on the types of data, types of insights and how these are visualised. The way physical and virtual assets are linked can be achieved through wired connections (e.g. Ethernet) or wireless connections (e.g. Wi-Fi). The network coverage for accessing physical and virtual assets (e.g. PAN, LAN, or WAN) depends on the physical asset's

characteristics, DT purpose, and environmental conditions. Once the connection has been established, data processing (e.g. filtering process, AI-based processing, data analytics, etc.) may be required to transform the raw data into a usable format for physical-to-virtual mapping or virtual-to-physical optimisation. The question to address is Q8: '*What are the network specifications?*' and '*What approaches should to be employed to process the data?*'.

3.7. Step 7: DT verification and validation

The DT needs to be verified to ensure that it accurately mimics the behaviour of its physical counterpart with a minor, acceptable discrepancy. A series of checks can be conducted on the physical asset, network communication, and virtual asset. This examination is designed to ensure proper integration of data and models, confirming that both assets exchange data according to the specified requirements. This includes assessing the DT's capacity to provide the desired insights and implement action plans effectively. The question to address is Q9.1: '*Is the model right?*'.

Considering the purpose of DT development, as defined in Step 1, one should follow a systematic process for DT validation. Unlike verification, which assesses if the DT has been built according to its specification, validation is undertaken to confirm if the DT effectively serves its intended purpose. Validation typically involves real data measurement to quantify improvements in the control process, decision-making, process planning, design, maintenance, and all aspects of value-generated activities. There are five essential steps for DT validation: (i) formulating the hypothesis, outlining the expected improvements or outcomes compared to traditional or existing methods; (ii) identifying the metrics to measure performance differences between the DT and traditional methods; (iii) applying a 'like-for-like' comparison to ensure equivalent contexts during the testing of the DT and its physical counterpart (e.g., the user groups for DT and its physical counterpart should be from the same population); (iv) selecting the appropriate statistical method to analyse empirical data results; and (v) evaluating if the observed performance improvement from using the DT is statistically significant. This validation process aims to ensure that the DT effectively fulfils its purpose, achieves predefined objectives, and aligns with stakeholders' requirements. The question to address is Q9.2: *'Does the DT meet the requirements?'*.

4. Case study

The proposed DT development framework was successfully applied to create a DT for a real-world use case in collaboration with Babcock International specialising in aerospace, defence and nuclear engineering services. The focus of the project was on five interconnected air compressors situated at the Connected Facility[2] at Devonport Royal Dockyard. These air compressors play a crucial role in compressing free air from the atmosphere to achieve the required pressure levels, following the specifications provided in the IWA 33–1:2019(en) standard, section 9.4.2.1. To enable real-time monitoring and data collection, sensors were installed on the air compressors. These sensors collected data at regular intervals of 60 s, allowing for continuous monitoring of the compressors' performance and operational parameters. The development of the DT, as outlined in Sections 4.1–4.2 and illustrated in Fig. 4, followed a structured three-stage process including: i) DT conceptual design development; ii) DT implementation; and iii) DT verification and validation.

[2] https://www.mottmac.com/article/79445/devonport-royal-dockyard-facility.

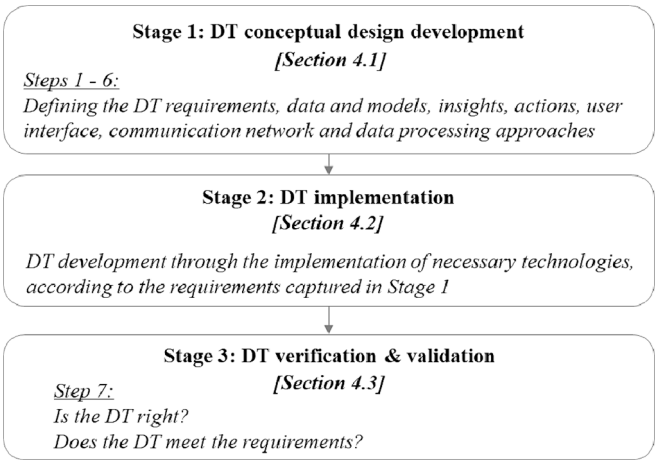


Fig. 4. Three-stage process for the DT development.

4.1. Stage 1: DT conceptual design development

The conceptual design stage plays a significant role in acquiring information and establishing the specifications of the DT. To effectively capture and define the DT requirements, a series of workshops were conducted involving various stakeholders, including engineers, facility managers and plant managers from the industrial partner. These workshops aimed to foster a shared understanding of the DT's purpose, features and vision for driving improvements and enhancing current processes. The proposed framework served as a guiding principle throughout the DT development process. Appendix I contains DT templates that were utilised to facilitate the capture of DT data, models, insights and visualisations. These templates provided a structured approach for comprehensively documenting the necessary requirements for the DT. Thus, the conceptual design stage served as the foundation for subsequent stages of DT development, ensuring the creation of a tailored and effective DT solution for the industrial partner.

4.1.1. Step 1: Defining the DT requirements

The first step in the development of the DT focuses on establishing a clear definition of the DT's scope and requirements. To achieve this, two online workshops were conducted, each lasting one hour, where key questions were raised to address the overall purpose of the DT, the modules to be included, the required functions of these modules, the expected improvements and the interconnections between the modules (i.e. the interface(s) of each module with other modules). These workshops facilitated a comprehensive understanding of the intended objectives of the DT and allowed for the refinement of its requirements, providing valuable guidance for subsequent development stages.

Fig. 5 provides a summary of the DT requirements, highlighting the identification of four modules during the workshops. These modules show the necessary functions of the DT and outline the expected improvements as well as the interdependencies with other DT modules. The number of modules may vary based on the complexity level of the twinned physical system. In systems where there are numerous DT modules, a structured approach becomes essential to assess the importance of each module and strategically determine their development sequence.

To analyse the fulfilment of DT requirements and prioritise each module, a modified House of Quality (HoQ) approach was employed. In this approach, the expected improvements of the DT are considered as customer needs, while the DT modules (i.e. technical descriptors) served as engineering parameters to meet these needs. The relationship between customer needs (represented vertically) and engineering parameters (represented horizontally) was assessed to evaluate the impact of each DT module on the expected improvements. Impact levels were

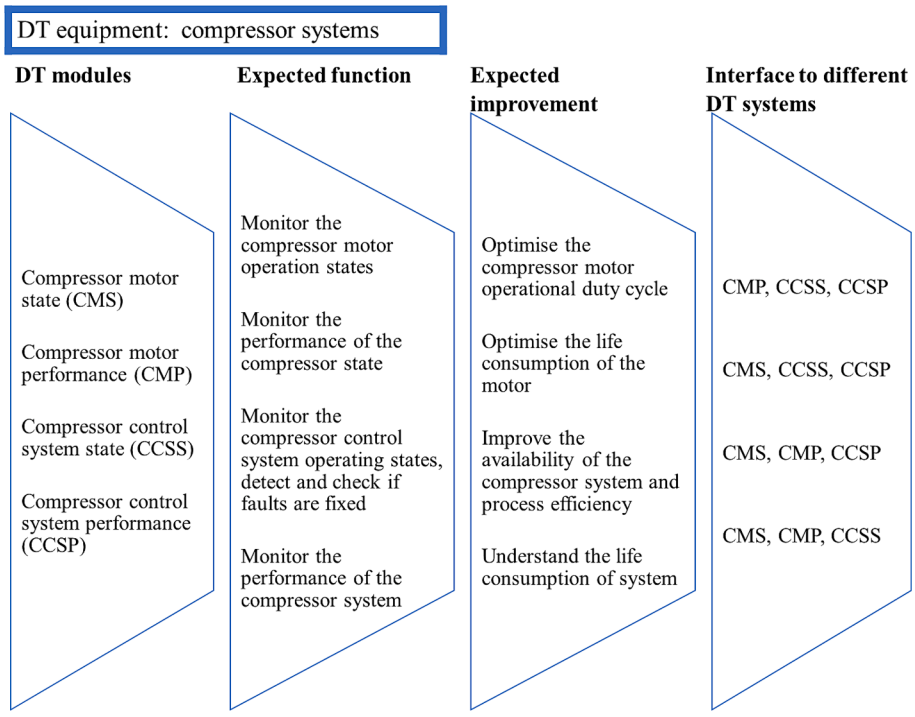


Fig. 5. DT requirements for the compressor system.

categorised into four scores: none (score 0), low (score 1), medium (score 3) and high (score 5). The scores for each DT module were aggregated and multiplied by the customer importance rating to calculate the total score. Based on the total scores, the modules were ranked, with the Compressor Control System State (CCSS) module identified as the most impactful, followed by Compressor Motor Performance (CMP), Compressor Motor State (CMS) and Compressor Control System Performance (CCSP). The prioritisation results of the compressor system are presented in Table 1 using a modified HoQ tabular format. Therefore, based on the prioritisation results obtained from the HoQ analysis, the DT development will focus on the CCSS module.

4.1.2. Step 2: Determining the DT data and models

In this case study, the primary objective of the DT development of the CCSS module is to improve the availability of the compressor system and enhance process efficiency at the equipment level. This will be achieved through effective operation monitoring and maintenance practices, which will enable a better understanding of the facility's operation, enhance decision making processes by promptly detecting faults and facilitate the capture and sharing of valuable data knowledge. Following the requirements identification in Step 1, the workshop proceeded by mapping the data and models required to support the functionality of the DT CCSS module. This mapping process was conducted in collaboration with domain experts from the industrial partner, who provided valuable insights and expertise in the field.

For each module, the necessary DT data and models were identified, along with their data sources, constraints and interfaces. However, for the purpose of demonstrating the requirements mapping, only the DT data and models for the CCSS module are presented in Fig. 6. The figure illustrates the various types of data sourced from sensors and controllers, along with their constraints and interfaces. However, data collection alone is not sufficient to support the functionality of the CCSS module. It is also necessary to develop DT models for the operating process of the

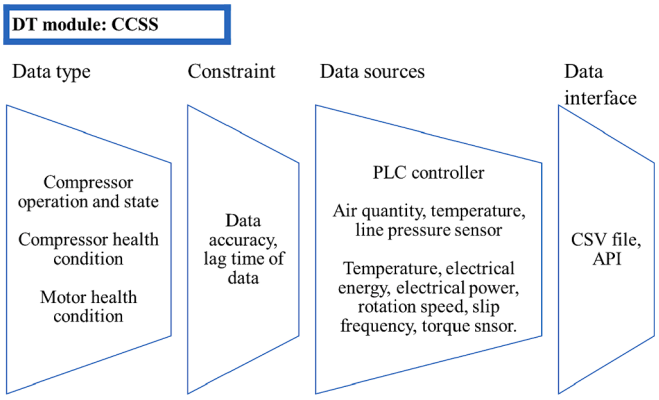


Fig. 6. DT data for the CCSS module.

Table 1
Prioritisation of DT modules using a modified HoQ.

No. of customer needs	Technical descriptors (engineering parameters) Direction of improvement: U (under) /D (down) /N (none) No. of technical descriptors	Customer importance rating	CMS U 1	CMP U 2	CCSS U 3	CCSP U 4
1	Optimise the operating hours and maintenance schedules of compressor motor	5	9	9	9	3
2	Optimise fault detection and maintenance schedule	5	9	9	9	9
3	Improve availability of compressor control system and process efficiency	5	1	3	9	1
4	Understand life consumption of system	5	3	3	9	9
	Importance (total)		**110**	**120**	**180**	**110**
	Rank		**3**	**2**	**1**	**3**

CCSS and fault detection system to process the collected data and facilitate the simulation of different scenarios. Since these models were not available, suitable modelling approaches needed to be identified. In this case, the agent-based modelling (ABM) approach was selected as it offers a bottom-up modular approach that supports the development of the DT module in a flexible, interactive and effective manner [35]. This approach, which effectively capturing probabilistic variability and dynamism in parallel interactions, allows for the construction of models that represent the behaviour of individual modules (i.e. agents) within the system, enabling a detailed understanding of the CCSS operating process. Considering potential technical and commercial constraints, the AnyLogic software package was selected to develop the agent-based simulation model for the CCSS module. Fig. 7 provides an overview of the DT models required for the CCSS module.

To gain a comprehensive understanding of the data required for the development of DT models, Table 2 summarises the raw sensor data for each compressor asset. The table includes descriptions of the data, data types and units where applicable. This information provides an overview of the data points that need to be collected and processed to support the DT models' development. In addition, the development of the DT models involves capturing the operating state logic, fault detection and repair logic of the compressors. The compressors can be in one of the following states: off (no operation), ready (for use), operating (operation started; no air released) or on load (compressing and releasing air). Each state has specific conditions and associated data types as outlined in Table 3.

Additionally, five types of faults along with their triggering conditions and associated data have been identified and listed in Table 4. It is noted that a fault is diagnosed if the fault conditions persist for more than 120 h and it is considered rectified or repaired if the asset returns to normal operational conditions for at least 72 h. By incorporating these logic and fault detection mechanisms into the DT models, accurate simulations of the compressor's behaviour and fault scenarios can be achieved.

4.1.3. Step 3: Determining the desired DT insights

Determining DT insights involves generating meaningful information that can be directly realised to achieve the desired improvements. This process goes beyond merely mirroring the physical system, as the DT integrates data from diverse sources, including sensors, models and visualisations, demonstrating feedback from the digital to the physical system. Through data analysis, this integration generates valuable information that can be promptly transferred to the physical system in real-time. The insights derived from the DT enable productive feedback, allowing for actions such as resource reallocation, task rescheduling, layout reconfiguration and other improvements that can optimise the operational efficiency. Fig. 8 presents the insights that can be derived from the DT data and models of the CCSS module. These insights focus on two aspects: the operational utilisation and fault detection of the compressors. The types of data required for the analysis that will be conducted automatically using the AnyLogic software are also included in Fig. 8.

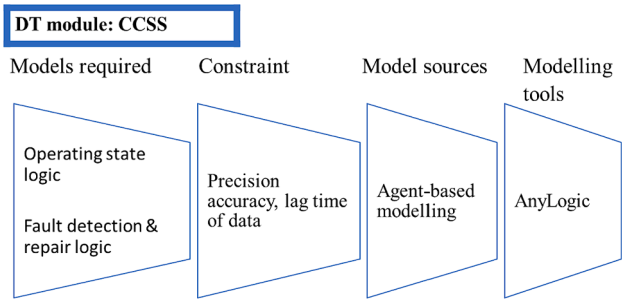


Fig. 7. DT models for the CCSS module.

Table 2
Column headers of captured data.

Column headers	*Description/ Data Type/ Unit*
ID	Unique identification number/record
Compressor	Name of the asset compressor
_time	MM/DD/YYYY HH:MM:SS
Air_Quantity	[0.1 m^3/h]
On_Load_Hours	Hours [H]
Ready_Hours	Hours [H]
Final_Temperature	[0.1C°]
Operating_Hours	Hours [H]
Line_Pressure	[0.001 bar]
Electric_Power	[0.01 kW]

Table 3
Types of states and conditions of compressor.

State	*Type of data*	*Condition*
Off	On Load Hours	0
	Operating Hours	0
	Ready Hours	0
Ready	On Load Hours	Static
	Operating Hours	Static
	Ready Hours	Increasing
	Air quantity	0
	Final temperature	< 30 °C
Operating	On Load Hours	Static
	Operating Hours	Increasing
	Ready Hours	Static
	Air quantity	0
	Final temperature	30 – 60 °C
On load	On Load Hours	Increasing
	Operating Hours	Static
	Ready Hours	Static
	Air quantity	318.4 m^3/h
	Final temperature	60 – 100 °C
	Electric power	260 – 290 W

Table 4
Types of faults and conditions of compressor.

Fault	*Type of data*	*Condition*
1. High temperature	Final Temperature	> 95 °C
2. High temperature due to air cooler blockage *Note: replacing the cooler at 95* °C	Final temperature	85 – 95 °C
3. Piston failure – air is continuously compressed (cannot change from 'on load' to 'operating' state)	Line pressure Electric power	> 7.8 bar 260 – 290 W
4. Electric overload	Electric power	≥ 310 W
5. Load piston failure:		
a. *air is not compressed*	Line pressure Electric power	< 6.9 bar < 100 W
b. *piston is overloaded*	Line pressure Electric power	≤ 6.9 bar ≥ 310 W

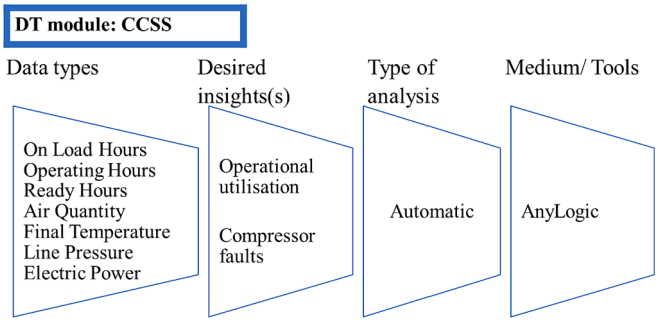


Fig. 8. DT insights of the CCSS module.

The insights will be derived from the DT will provide operators with a comprehensive understanding of their facility's operations, allowing them to promptly detect operational anomalies and identify areas for further improvement. By acting upon these insights, operators can enhance the availability of the compressors, optimise resource utilisation and streamline operations, hence, improving the overall system's performance.

4.1.4. Step 4: Building the DT user interface

The DT insights determined in Step 3, focused on measuring operational parameters and detecting faults in the selected use case, serve as a basis for initiating maintenance actions and making adjustments to the control process. To effectively monitor these insights and make informed decisions, 2D and 3D visualisations on a dashboard will be developed using AnyLogic and Unity software platforms. Fig. 9 outlines the requirements for the visualisation of the CCSS module, ensuring that the essential information is presented in a visually appealing and user-friendly manner. The 2D visualisation development will be carried out using AnyLogic, which offers tools for creating 2D graphs, charts and diagrams to present the DT insights in a clear and intuitive manner. In addition, Unity will be utilised for developing the 3D visualisation, taking advantage of its capabilities to create realistic and immersive visual environments. By utilising both platforms, compelling and informative dashboard visualisations will be developed. Operators and facility managers can efficiently monitor the performance of the compressors, quickly identify anomalies or deviations and take timely actions to optimise the compressors' performance. Comprehensive and intuitive visual representations will also enhance operational efficiency and ensure the smooth operation of the compressors.

4.1.5. Step 5: Developing the DT actions

The insights obtained from Step 4 and visualised in Step 5 are intended to provide actionable information that supports facility operators and managers in making informed decisions to enhance the efficiency, availability and overall performance of the five compressors. These insights will enable a better understanding of the supply and demand dynamics of the compressors. By integrating and analysing this aggregated information, domain experts can derive optimal parameters for system improvement. Furthermore, since multiple compressors operate simultaneously to meet the demand for pressurised air, the CCSS module can provide valuable insights for detecting faults. Early detection of faults allows operators to proactively schedule maintenance activities, minimising unexpected downtimes and optimising system availability. To address specific faults, condition-action rules can be established. For example, if a fault is diagnosed in the cooler or thermostat, the corresponding action would involve replacing the faulty component. These actions are performed manually by the operators, guided by the insights provided by the DT. By utilising the insights generated by the DT and implementing appropriate condition-action rules, operators can proactively improve the system's performance, optimise control processes and ensure the availability of the compressors. This can ultimately lead to enhanced operational efficiency, supporting the achievement of performance objectives.

4.1.6. Step 6: Building the DT communication network

To ensure smooth synchronisation between the physical asset and the DT, establishing seamless, real-time and bi-directional communication is essential. In the context of the CCSS module, the network communication requirements, as depicted in Fig. 10, are identified to facilitate a secure and reliable connection. The communication links include the internet wide area network (WAN), which connects multiple local area networks (LANs) and the wireless LAN, which enables communication between Wi-Fi connected devices in a personal network. These links provide the infrastructure for data transmission and facilitate the exchange of information between the physical asset and the DT. For efficient data communication, a web server will be created to support the development of Representational State Transfer Application Programming Interfaces (REST APIs). RESTful APIs utilise the Hypertext Transfer Protocol (HTTP) for accessing and manipulating data through operations such as creating, reading, updating and deleting resources. This approach will ensure effective and standardised data exchange between the compressor control system and its DT. The widely adopted HTTP communication protocol will be used to fetch resources, such as HTML documents, over the internet. HTTP follows a client–server architecture, where requests are initiated by the recipient, typically a web browser. In achieving a near real-time aspect of DT communication, update intervals of 20 min were implemented, a frequency determined based on insights from experts operating the air compressor systems. This selection was influenced by the nature of the system; typically, state changes require more than 20 min to occur. Additionally, we considered that a slight delay in fault detection poses minimal risks to the facility and personnel, with negligible impact on decision-making processes.

The selection of appropriate bandwidth (i.e. the capacity of data that can be transferred per second), latency (i.e. to the time delay between data transmission and reception) and coverage (i.e. the geographical area covered by the network of a service provider) will depend on the capacity and capabilities of the service provider capacity and the design intent of the DT. To ensure network security, measures such as Wi-Fi Protected Access 2 (WPA2) and firewalls will be implemented. WPA2 provides encryption and authentication protocols for securing Wi-Fi networks, while firewalls act as network security systems to protect against unauthorised access and maintain data integrity and confidentiality. By meeting these network communication requirements and implementing robust security measures, the CCSS module of the DT can effectively communicate with the compressor control system, enabling seamless integration and real-time exchange of information between the two entities. This will enable operators and managers to monitor and control the compressor system reliably and securely, enhancing operational efficiency and enabling data-driven decision-making.

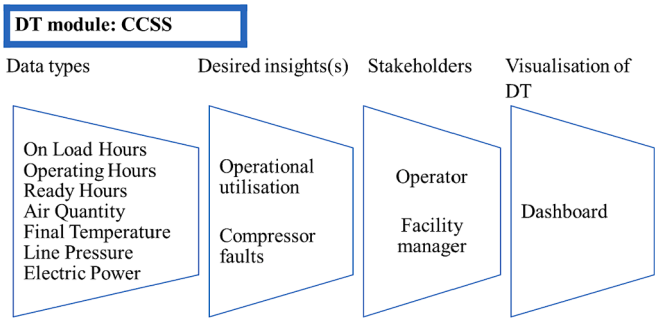


Fig. 9. DT visualisation of the CCSS module.

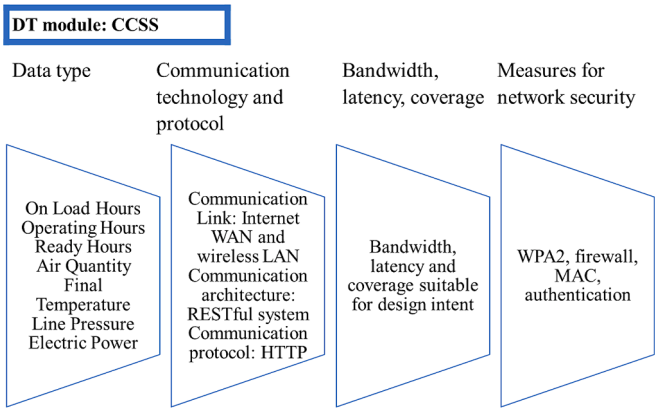


Fig. 10. DT communication network of the CCSS module.

4.2. Stage 2: DT implementation

This stage focuses on the DT development, implementing suitable technologies based on the requirements identified during the conceptual design phase (Stage 1). The selected technologies are carefully chosen to ensure compatibility with the existing infrastructure and data management systems of the industrial partner. Fig. 11 illustrates the data process, ranging from data collection to realisation, for implementing the DT in the specific use case. The emphasis in this stage lies on the practical implementation of DT technologies, providing a clear and systematic approach that aligns with the industrial partner's infrastructure and requirements. The objective is to enable the successful integration of the DT into the existing system, facilitating its effective utilisation and maximising its benefits.

4.2.1. Data collection

In the design specification of the CCSS module, data, obtained from sensors and actuators, is essential for its operation. The digitalisation era offers a range of options for data collection, including IoT-based sensors, data acquisition systems, and computer networks, enabling the transformation of traditional factories into Industry 4.0 factories [51]. For the compressor system in the industrial facility, a data sensing infrastructure has already been implemented, connecting to the Siemens MindSphere cloud platform. The MindSphere platform serves as a commercial solution for managing data collection and storage, providing remote access to the data through the use of MindSphere APIs. These APIs allow for seamless integration with the data sensing infrastructure, enabling the automated collection and storage of relevant data. To facilitate the automated collection of data from various sources in the CCSS module, Python scripts version 3.9.5 were developed using Visual Studio Code, a popular integrated development environment (IDE). These scripts enable acquiring real-time data, such as temperature, pressure, air quantity and other relevant parameters, from the sensors and actuators installed in the compressor system. The collected data is then stored in the data storage of the DT. Further details regarding the DT data storage will be discussed in Section 4.2.2.

4.2.2. Data storage

Sharing data across different proprietary platforms can be challenging due to variations in standards and protocols, especially when data originates from distributed heterogeneous systems [101]. The lack of interoperability between systems can impede seamless data exchange and integration, limiting the potential benefits of DTs. To address this challenge, a unified data storage solution has been implemented for the CCSS module. Additionally, the selected data storage system must be scalable and adaptable to accommodate the evolving nature of the DT in parallel with its physical counterpart [23,102]. Unlike traditional SQL databases that rely on a fixed schema, NoSQL databases provide horizontal scalability and flexibility in data structure [103]. MongoDB, an open-source NoSQL database with a growing development and support community, has been chosen as the preferred solution for the DT data storage. MongoDB provides the capability to handle large volumes of data, support flexible data models and facilitate efficient data retrieval and querying. By implementing MongoDB as the DT data storage solution, the CCSS module can effectively manage and store the data from diverse sources, ensuring scalability, adaptability and seamless integration of data.

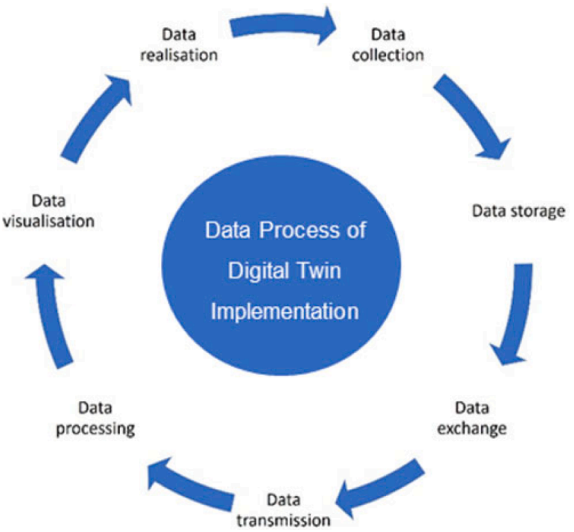


Fig. 11. Data process of DT implementation.

4.2.3. Data exchange

Ensuring continuous and simultaneous data flow across the different software systems of the CCSS module (i.e. MindSphere cloud, AnyLogic and Unity) requires to establish a generic data structure and standardised data interfaces for seamless data exchange. The use of ontology plays a crucial role in achieving this objective and Protégé was employed in this case study to create the information model for the DT CCSS module. Fig. 12 illustrates the UML class diagram of the ontology for the CCSS module. The ontology design for the CCSS module follows the proposed DT development framework. Each asset (e.g. air compressor) at the equipment-level is part of a factory or facility, whereas can have data sources, modules and visualisations. Each air compressor asset generates a CSV file that serves as a data source, containing raw sensor data with various parameters such as unique record IDs, timestamps, air quality, on-load hours and line pressure, as listed in Table 2.

Each module can facilitate interconnections within other modules of the DT and provide insights. For instance, the CCSS module may have interfaces to different modules such as the CMS and CMP modules. These interfaces allow for the exchange of data and information between the modules, enabling a comprehensive analysis of the compressor's performance and condition. Additionally, the CCSS module offers real-time or selected-date insights regarding the state and fault conditions of the compressor.

These insights include information such as fault detection time, fault condition, recommendations for handling the fault, maintenance or control adjustments, repair status. The CCSS module derives these insights by processing diverse data sources and allows for real-time or specified range value retrieval. The asset can be also visualised using Computer-Aided Design (CAD) models to enhance the understanding and representation of the compressor system.

A simplified representation of the data exchange process followed for the CCSS module is presented in Fig. 13. The transfer of data from the MindSphere cloud to MongoDB is facilitated by a Python script, utilising the PyMongo package and MindSphere APIs. In MongoDB, data for each asset is stored in separate databases, with collections representing different data sources for each asset.

This database structure in MongoDB allows for easy integration of new data sources for existing assets or creation of a new database for additional assets. When new data sources are introduced for existing assets, they can be seamlessly incorporated into the existing database without requiring extensive modifications to the structure. Similarly, if new assets are introduced, new databases can be created within the MongoDB model to accommodate them. This flexible structure enables efficient aggregation of data across collections within each database and enables the retrieval of desired data, when needed, through the use of APIs. As a result, this data exchange approach offers scalability by incorporating new data sources, while minimising the need for significant modifications to the existing infrastructure.

To enable the data communication between the different software systems, a web server was developed using the FLASK micro web framework, which is a Python-based framework. FLASK-RESTful [104], an extension of FLASK, was employed to quickly build REST APIs for

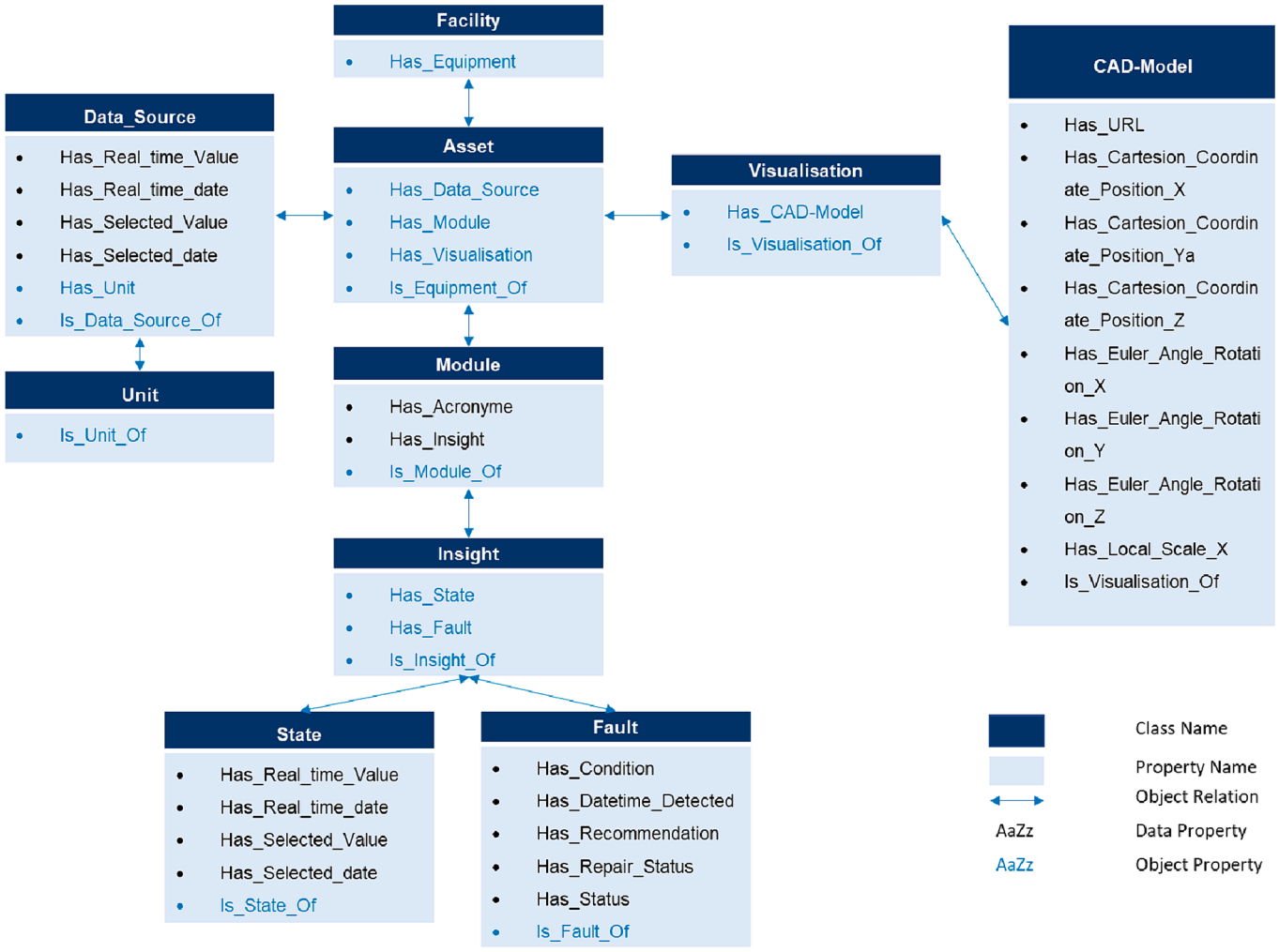


Fig. 12. UML class diagram of the ontology for the DT CCSS module.

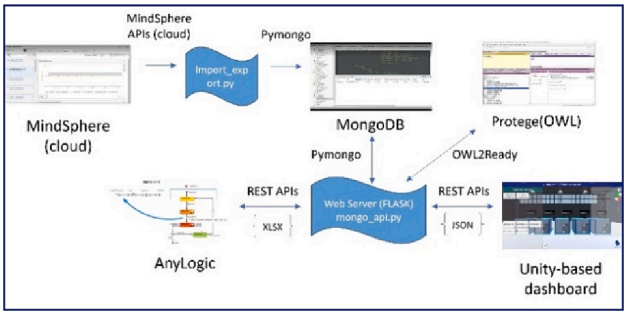


Fig. 13. Data flow across MindSphere, AnyLogic and Unity.

performing CRUD operations (Create, Read, Update and Delete) on data endpoints. The data structure within the ontology was established using Owlready2, a Python module designed for ontology-oriented programming. Owlready2 provides functionalities for manipulating ontology files, including loading OWL files and creating and manipulating classes, properties and instances. Reasoners such as HermiT or Pellet can be employed for automatic reclassification [105]. The combination of PyMongo and Owlready2 enables the addition of assets to the DT. PyMongo facilitates data retrieval and manipulation from MongoDB, while Owlready2 supports ontology management and reasoning. Integrating these packages allows for the creation of assets in the DT that accurately represent real-world objects and their relationships. This ensures seamless integration of diverse data sources and maintains the DT's alignment with the physical assets. Furthermore, the data of existing individuals can be directly modified according to the selected data. When data is updated in MongoDB, a generic function is used to replace the previous data in the ontology with the latest data from the assets stored in the database.

The data structure of MongoDB is designed to align with the ontology structure created for the DT, allowing data to seamlessly flow between different systems using common data structures and interfaces. A sample of the data structure in OWL format is shown in Appendix II, representing an instance of Data_Source. This data can be transformed into an open standard data format file, such as JavaScript Object Notation (JSON), using FLASK API, allowing access by the Unity-based dashboard. In the case of AnyLogic software, it offers Cloud APIs in Python for compatibility with other programs and processing of JSON files, although this feature requires a commercial licence. Alternatively, the common file format for data exchange in this case study is Microsoft Excel Open Extensible Markup Language Spreadsheet (XLSX), which is supported by AnyLogic. Fig. 14 illustrates the DT data access and infrastructure, depicting the systems and processes involved in acquiring and managing the data within the DT environment. This infrastructure includes various components, such as data sources, databases, APIs and connectivity mechanisms that enable the collection, storage and retrieval of data for analysis and visualisation.

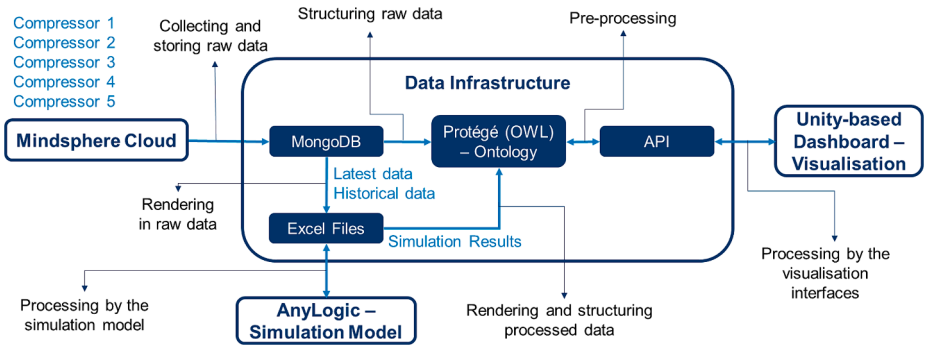


Fig. 14. DT data access and infrastructure.

4.2.4. Data transmission

In this case study, data transmission occurred between different devices for the CCSS module development. The setup involved running a web server and MongoDB on one device, which had an Intel® Core™ i7-8750H CPU @ 2.2 GHz 2.21 GHz and 15.5 GB RAM installed. On separate devices, AnyLogic was run on an Intel® Core™ i5-8250U CPU @ 1.60 GHz 1.80 GHz with 24.0 GB RAM and Unity was run on an Intel® Core™ i7-8750H CPU @ 2.2 GHz 2.21 GHz with 15.5 GB RAM. These devices were chosen to ensure sufficient computing power for the simulation and visualisation tasks, respectively. The network communication was tested using the high-speed wireless networking standard IEEE 802.11ac. This standard provides reliable and efficient wireless connectivity for data transmission. To ensure seamless and secure communication, the TCP/IP protocol suite, a widely adopted network protocol, was employed. The TCP/IP protocol suite enables the smooth and efficient transfer of data between different devices and ensures reliable delivery of data packets over the network. By employing these standards and protocols, the CCSS module achieved robust and efficient network communication capabilities.

During the data transmission process, the raw data stored in MongoDB was converted to XLSX format. For each asset represented in the database, an Excel file was created, along with an additional file denoting the period of data extraction. The real-time data files averaged around 6 kb per asset, while the size of historical data files varied depending on the extraction period. For instance, an eight-day period resulted in approximately 500 kb per file. The file representing the extraction period date had a size of approximately 10 kb. Furthermore, the Excel file with the simulation results for the five compressors had a storage space of approximately 7400 kb.

4.2.5. Data processing

In the data processing stage, the raw sensor data collected from MindSphere Cloud is transferred through two distinct flows. In the first flow, the data is imported from MongoDB to the Protégé ontology, where corresponding individuals in the ontology, such as fields 'Has_Real_time_Value' and 'Has_Real_time_date' are updated for each compressor asset. These fields represent real-time values of operating parameters and dates obtained from the database for each asset. This process enables the visualisation of data through the data source class depicted in Fig. 12. The second flow exports the data form MongoDB into XLSX files, with each file containing data for one air compressor. These files were processed using AnyLogic, applying the logic from Table 3 and Table 4. This allows for an accurate representation of the compressors' behaviour and generates insights on their operating states and fault status. The simulation model developed using the ABM approach enables the modelling of the state and fault behaviour of the compressors as individual agents. By employing the ABM approach, the DT achieves a scalable, flexible and detailed representation of the compressors' behaviour, facilitating the analysis of various scenarios.

The simulation results were then exported from AnyLogic into an XLSX file. This processed data can be matched with the corresponding individuals in the ontology. These include fields representing operating values and timestamps (i.e. 'Has_Real_time_Value' and 'Has_Real_time_date') as well as fault detection conditions and timestamps (i.e. 'Has_Condition' and 'Has_Datetime_Detected'). The ontology serves as the central format for the data structure, acting as both an input flow for data sources and an output flow for visualisation interfaces. The ontology's structure, depicted in Fig. 12, was primarily used as the format for data representation. However, to facilitate data reading and transmission, the ontology was converted into various formats, such as JSON or XLSX. Ultimately, the data was imported into the OWL format, serving as the final storage format in the ontology. In terms of the repair mechanism, the DT allows users to modify and update the repair procedures through the DT visualisation's user interface. This feature empowers field operators to incorporate new knowledge and insights, enhancing the repair procedures for the compressors and improving overall system performance and reliability. This feedback loop enables a continuous improvement process, where the DT serves as a platform for operators to actively contribute to optimising repairs based on their practical experience and real-time observations. The ability to adapt and refine repair procedures through the DT empowers operators to proactively address issues, minimise downtime and maximise the efficiency of the air compressors.

4.2.6. Data visualisation

Two dashboards were developed using AnyLogic and Unity to visualise the insights obtained from the simulation. The 3D representation of the compressor station within the industrial facility's shop floor layout, created using AnyLogic, is presented in Appendix II, providing an overview of the physical arrangement of the compressors. The insights obtained from the AnyLogic simulation model are presented in Appendix II, presenting the state, date, time, temperature, on-load hours and air quantity of the five air compressors. This visualisation enables operators to monitor and assess the current operating conditions, demand, and availability of each compressor. Appendix II shows the daily and monthly line pressure and final temperature of the compressors over time, offering a comprehensive view of the variations and trends in these key parameters. This visualisation can help operators in analysing the performance patterns and identifying any potential issues or anomalies. In addition, Appendix II illustrates the type of fault, if detected, along with the fault detection date and time, recommended repair action and the repair status of the air compressor AC2. This visualisation aids in the identification and management of faults, enabling operators to take prompt repair actions and, hence, minimise downtime.

Furthermore, the results from AnyLogic were also visualised in Unity, providing a more interactive and immersive visualisation experience, allowing operators to easily access and interpret the DT insights. The Unity-based dashboard provides a user interface designed for asset monitoring, fault detection, and feedback provision to the DT. Fig. 15 illustrates the user interface for asset monitoring, providing information

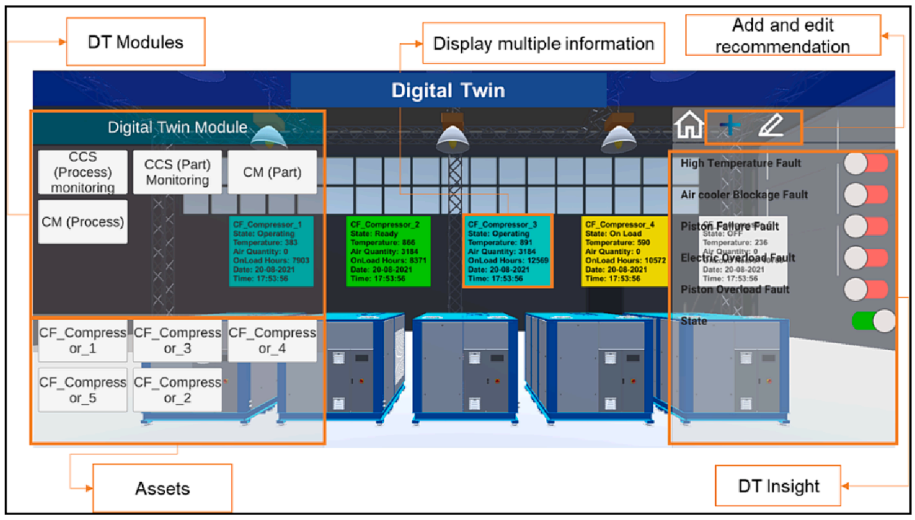


Fig. 15. DT visualisation: User interface for asset monitoring (state, demand and availability of the five compressors).

on the state, demand and availability of the five compressor assets for the CCSS module. Appendix II presents the user interface designed for asset fault detection, providing operators with comprehensive information regarding the fault type, condition and recommended repair actions for each compressor. This visual representation allows operators to quickly identify and understand the specific faults affecting the compressors. For instance, in Appendix II, an electric overload fault has been detected in compressor AC5 and has persisted for a minimum duration of three days. This information enables operators to prioritise and plan the necessary repairs effectively. Fig. 16 presents the user interface for providing feedback to the DT, enabling operators to contribute their insights and observations by adding and editing recommendations. This tacit knowledge, related to repair actions, steps to be followed, commonly encountered failures and challenges in the repair process, helps operators actively participate in the continuous improvement of the physical asset's performance (i.e. bi-directional communication of data). For example, in Fig. 16, if the repair actions are not carried out within the specified timeframe, it is advisable to contact a technician for further assistance. This feedback mechanism allows operators to share their expertise and practical experience, hence, enhancing the DT's capabilities and improving its ability to address similar situations in the future. The feedback provided by the facility operators through the user interface in Fig. 16 is captured and integrated into the Protégé ontology. This valuable feedback can be reused in similar scenarios, further enriching the knowledge base of the DT. Capturing the operator feedback into the ontology, the DT becomes more robust and effective in handling faults and optimising the repair actions.

These user interfaces, in both AnyLogic and Unity, facilitate efficient monitoring, fault detection, and the execution of repair actions of the compressors. These interfaces offer a comprehensive overview of the compressor system's performance, promoting collaboration between

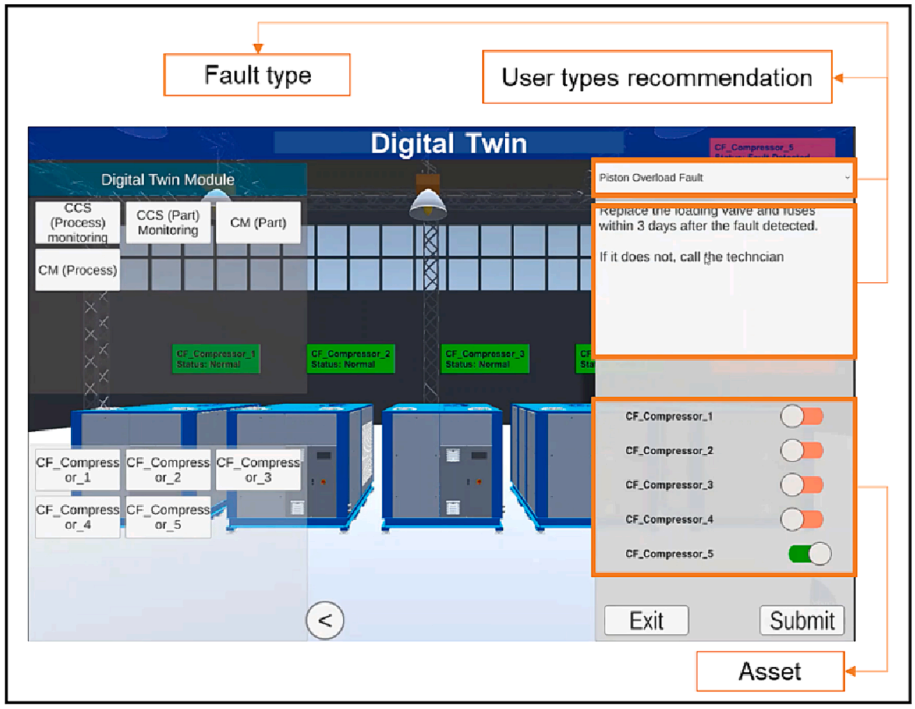


Fig. 16. DT visualisation: User interface for providing feedback to the DT to realise continuous improvement to the physical asset.

operators and the DT. Through this iterative feedback loop, these visualisations can enhance data-driven decision-making, reduce the potential for human-error, support system optimisation and enable continuous improvement of the physical compressor assets based on real-time insights.

4.2.7. Data realisation

In the context of the CCSS module, manual data realisation refers to the process of translating the insights and recommendations provided by the DT into actionable steps. The iterative process of data and model identification within the DT ensures that the CCSS module accurately represents the behaviour and functionality of the compressor control system. The DT enables real-time and historical monitoring of the compressor control system's state and the detection of various faults that may occur. When a fault is detected in one of the five compressors through simulations and data analysis, operators and managers, as captured in Section 4.1.5 interpret the results and determine the appropriate repair actions to be taken. The data realisation in this scenario is primarily a human-driven process. These actions, outlined in Table 5, are tailored to address the identified faults in the context of the CCSS module for the compressors. For instance, if a fault is identified such as high temperature (i.e. exceeding 95 ^{O}C), the recommended repair action, dynamically adapting based on feedback from the DT, is to replace the static valve. Additional actions can include preventive maintenance activities, adjustments to operational parameters or implementing process improvements.

The responsibility for executing these repair actions lies with the operators or managers responsible for the operation and maintenance of the compressors within the facility. They rely on the insights and recommendations provided by the DT to guide their decision-making and ensure the proper functioning and performance of the compressors. Manual data realisation also requires relevant skills and expertise to evaluate the outputs of the virtual twin and apply them effectively to the physical compressor asset. By incorporating manual data realisation in the CCSS module for the five compressors, the operators can effectively address faults and perform the necessary repairs to optimise the performance and reliability of the compressor control system. The iterative nature of the DT allows for continuous improvement and refinement of the repair actions based on real-world observations and feedback.

4.3. Stage 3: DT verification and validation (step 7)

The verification of the CCSS module consisted of multiple aspects to ensure its accuracy and reliability. Firstly, the physical compressor asset was checked for proper functioning. This involved assessing whether the sensors were installed correctly and measuring the right data, which was stored accurately in the database. Additionally, it was essential to validate that the DT read the correct data from the database without any errors in the data reading process. The data processing phase was also examined to ensure that the right data was fed into the appropriate program or source code without any bugs or issues. Furthermore, the data visualisation accurately reflected the status and behaviour of the physical compressor and the DT read the correct data from the database for visualisation purposes. The speed and efficiency of data exchange between different subsystems were assessed and the insights provided by the DT were relevant and easily understandable by the facility's operators and managers. Finally, the operator's ability to recognise known situations from the DT and take appropriate actions based on the insights provided was evaluated. These verification steps have been applied to the CCSS module to ensure its accuracy, functionality and usability, establishing its alignment with the physical compressor asset it represents.

Furthermore, the CCSS module was validated in accordance with the requirements outlined in Step 1 (Section 4.1.1). The validation process involved a 1.5-hour workshop with key personnel from the Company, including the Head of Innovation (with more than thirty seven years' experience), the Group Head of Research and Partnerships (with more than thirty years' experience) and an Innovation Engineer (with more than ten years' experience). The workshop aimed to assess the effectiveness of the DT by simulating real-world scenarios and predicting the states and faults of the compressors. The objectives of the validation were to evaluate the ability of the DT to: (i) accurately monitor the operating states of the compressor, enabling a comprehensive understanding of the system operation; and (ii) promptly detect faults, improving the compressors' availability at the equipment level. Given that the company had not yet implemented DT in this facility, raw senor data, collected over an eight-day period, was used to test the DT's output values related to the compressor states and faults.

Two scenarios were examined during the validation process: Scenario 1 aimed to predict a 10-hour 'off' state for compressor 5 starting on August 13, 2021, at 10:00 am. Scenario 2 focused on detecting fault type 2, characterised by high temperatures caused by air cooler blockage according to Table 4. The fault occurred on August 16, 2021, at 18:02, and was resolved within a three-day timeframe. The validation successfully confirmed the accurate prediction of the 'off' state for compressor 5 and the prompt detection of fault type 2 based on the specified temperature conditions and repair timeline. However, a 60-second delay in fault prediction compared to real-time data was observed, which could be attributed to factors such as sensor lag time or internet connection issues. Future work should address this limitation. Nonetheless, the 60-second delay is not expected to significantly impact the results, as state changes typically require more than 20 min, and a slight delay in fault detection poses minimal risks to the facility and personnel, with minimal impact on decision-making processes.

In summary, the adoption of a DT in the industrial facility for the compressors could offer several advantages, including real-time monitoring of the compressor operation, prompt detection of faults, improved operational efficiency, reduced downtime, enhanced decision-making and maintenance cost savings. The positive feedback received from the industrial partner team during the workshop further validates the reliability and alignment of the results with historical data. The team also emphasised the significance of adopting an ontology-based approach for capturing and sharing valuable data knowledge, highlighting its role in enhancing the effectiveness of the DT. The insights gained from the validation process contribute to refining and enhancing the DT, ensuring its reliability and applicability in in real-world industrial settings. Continuous improvement of the DT will enable accurate and reliable monitoring of the compressors, ultimately leading to improved operational efficiency and maintenance practices.

Table 5
Fault types diagnosis and repair actions.

Fault type diagnosis	*Repair action*
1. High temperature (>95 °C)	Replace the static valve
2. High temperature due to air cooler blockage (<95 °C)	Clean the air filter
3. Piston failure – air is continuously compressed	Replace the loading valve
4. Electric overload	Replace the fuses & loading valve
5. Load piston failure:	Replace the loading valve

5. Discussion

Most of the existing literature on framework development for DTs in manufacturing is limited to conceptual models [4,11,106–108] or lacks the capacity for generalisation and, hence, reusability as the DT frameworks are exclusively designed for specific use cases [1,16]. Moreover, the existing literature highlights that the majority of attempts in developing DTs are capable of handling homogeneous data while lacking in effectively deploying scenarios of complex assets where data heterogeneity should be considered due to a large number of data sources [46]. In this regard, data integration methods such as ontology

to enable reasoning to relevant modules and processes in manufacturing assets are beneficial. This can enable the utilisation and exchange of a wide variety of data in a repeatable and relatively easily adaptable way [47].

Additionally, in the context of DTs in manufacturing, modelling and simulation techniques play a key role in capturing the dynamic behaviour of systems or processes through virtual representation [14,109]. The existing literature emphasises the development of conceptual models [37] and digital models or shadows [5,7,14], employing top-down approaches [38,58,91] that typically capture only the static complexity of systems while neglecting the aleatory uncertainty of resources (e.g. people, spares, facilities, etc.) [110]. In manufacturing, labour-intensive processes and random events taking place at different locations at the same time (i.e. parallel dynamic interactions) can greatly increase the complexity of systems. Advanced computational modelling including bottom-up ABM approaches can comprehensively capture the probabilistic variability and dynamism of such parallel dynamic interactions [50,111]. Compared to other dynamic modelling techniques such as discrete event simulation and system dynamics, ABM can provide greater modularity, adaptability, interactivity and autonomy for decision-making [52,53].

Moreover, standards under development by the International Standards Organisation (ISO), the Industrial Digital Twins Association (IDTA) and the Digital Twins Consortium (DTC) are poised to provide essential guidelines, methods and best practices for the development of DTs. ISO 23247 provides a generic DT development framework to help users select building blocks for DT implementation in manufacturing. This newly developed standard provides a generic, reusable and customisable, irrespective of implementation, framework so that it can support multiple use cases in manufacturing. However, ISO 23247 has not yet covered comprehensively the aspects of verification (i.e. DT is built right and the implementation is free of code errors), validation (i.e. DT is developed according to the requirements and meets its purpose) and uncertainty quantification (i.e. a measure of performance that users can apply as part of a credibility assessment of DT).

Transitioning to insights from industry reveals a significant impediment to the widespread implementation of DTs, especially in complex systems – the associated cost. Recognising the inherent inverse relationship between system complexity and ease of implementation, a standardised framework emerges as a promising strategy to mitigate implementation costs. This standardised approach, characterised by providing a shared roadmap and automating specific steps, holds the potential to streamline implementation, ultimately reducing costs and making DT adoption more feasible for industries dealing with complex systems. Furthermore, the industry emphasises the critical importance of addressing uncertainties surrounding returns on investment (ROI) from DTs. While a standardised implementation approach may yield efficiency gains, the diverse nature of systems implies a range of benefits. Quantifying these benefits remains a formidable challenge, and relying solely on a standardised approach may inadequately address the complexities of individual systems. However, the industry acknowledges that collaborative efforts are essential for developing methodologies to quantify and benchmark ROI. This industry-wide collaboration will help stakeholders make well-informed decisions about the adoption of DTs.

Addressing the aforementioned academic and industrial challenges, the novelty of this work lies in harmonising existing frameworks and unifying concepts and processes by introducing a unified generic framework with standardisation in the DT development. Encompassing common steps from requirements capturing to verification and validation, the framework offers the potential to mitigate implementation costs in complex systems. Unlike existing literature, this work presents a unified approach to address challenges in DT data management, such as heterogeneous data integration and continuous data flow, along with dynamic modelling through ontology integration and a bottom-up agent-based approach, respectively. More specifically, in the context of manufacturing, the proposed step-by-step framework contributes to the literature facilitating the development of DTs by capturing their requirements, determining the DT data, models and desired insights, developing actions, and enabling the composability of models and interoperability among modules. The framework provides a variety of options for data collection, modelling and simulation, analysis and visualisation of insights, network communication, integration, as well as DT verification and validation. An ontology that facilitates the scalability and flexibility of DT is proposed. The ontology is structured in such a way that can be easily extended if new assets, data sources or data types need to be added to the DT. The proposed ontology also plays a key role in information modelling enabling a continuous and simultaneous flow of data that can be processed by different subsystems using standardised data interfaces. The ontology can, thus, model information from heterogeneous sources in a reusable way.

This study goes beyond the existing conceptual research, by demonstrating the practical application and effectiveness of the proposed DT development framework through a real-industrial case study. It is noted that the selected case study effectively demonstrates the broad applicability of the proposed framework in a typical industrial setting with multiple assets and diverse operational states and faults. The successful implementation and validation highlight its potential for wider application in different industries. The proposed framework unifies existing DT frameworks merging concepts and process development in manufacturing while offering users reusability and scalability. Utilising the framework, DTs for complex manufacturing systems can be developed and analysed enabling a better understanding of the facility's operation, prompt detection of faults and potential avoidance of unwanted events such as interruption, energy loss or efficiency loss. Such well-structured step-by-step guidance can facilitate enhanced decision-making, leading to improvements in the efficiency, effectiveness and availability of complex manufacturing systems. The case study involved: (i) successfully applying the proposed DT framework to an industrial facility equipped with five compressors; (ii) demonstrating the ontology's ability to facilitate continuous data flow among data sources (MindSphere cloud), simulation software (AnyLogic) and visualisation platform (Unity), using standardised API interfaces; (iii) assessing the scalability of the ontology when new assets or sensors are integrated; and (iv) evaluating the DT's capability to provide insights into compressor performance and health, through fully automatic analysis using the agent-based simulation technique and to take actions via manual realisation where the engineers at the shop-floor are responsible to take control decisions while interacting with the DT. The results show that the DT can effectively identify the state of each asset over time, the performance based on the operating parameters and fault-repair status considering when, which asset and what type of fault has been diagnosed and if/when it has been repaired. The analyses of the results show that the proposed DT could help users recognise compressors' failure more quickly and accurately with the DT system compared to the non-DT system. Moreover, the DT condition-action rule informed by the DT could improve the availability of the compressors in comparison with the non-DT system. Thus, the DT can enhance decision-making through the prompt and accurate detection of faults enhancing the assets' availability.

6. Concluding remarks

This paper has presented a unified framework that systematically guides the development of DT, enabling reusability and scalability. The proposed framework harmonises existing DT frameworks by unifying concepts and process development in manufacturing. A step-by-step guideline for capturing the DT requirement(s) in each step is provided. The framework consists of seven steps, starting from the initial planning of the DT purpose and the identification of DT design elements through to the verification and validation steps to confirm that the DT purpose has been met. The proposed DT framework also enables the integration of heterogeneous data types and a continuous flow of information

among data sources, simulation models, and visualisation platforms. This is enabled by implementing an ontology into the framework, which also facilitates DT scalability. Furthermore, using a bottom-up approach, an agent-based simulation model is developed to monitor the operation of physical assets and automatically detect faults. The agent-based modelling approach enhances the flexibility, interactivity, and modularity of DT design.

To test the validity of the proposed DT framework, a case study of an industrial facility (Connected Facility at Devonport Royal Dockyard) with five low-pressure air compressors was employed. Following the proposed framework, a DT that can automatically and remotely monitor the operation and failure of the compressors has been developed. The results obtained from this DT were compared against data from the company, showing excellent agreement in terms of the operation and fault detection of the compressors. The analyses of the results demonstrate that the proposed DT can increase the availability of the facility's operation and enhance decision-making through the prompt and accurate detection of faults. The outcomes from the DT provide support and detailed information for the prompt and accurate detection of faults in complex systems. The DT framework can be used as a guide for DT development, enhancing informed decision-making and control in manufacturing sectors with a complex nature.

Further to this work, the applicability of the DT framework can be tested in other manufacturing or production systems, as well as in wider industries such as aviation, maritime, and oil and gas. Moreover, the proposed framework can be employed in different contexts to quantify the impact of the DT in terms of reliability, maintainability, productivity, and sustainability. Cost data could also be implemented into the simulation model to quantify the cost and benefits of various scenarios, including emergency events capturing their financial and environmental impacts. Additionally, the DT framework can be enhanced by considering guidelines for data integrity, security, and privacy, as well as incorporating machine learning techniques to promptly predict potential failures or the remaining useful life of assets. As we progress towards Industry 5.0, our future endeavours include establishing a collaborative human–machine environment. Our focus will be on automating machine feedback through control signal transmission, employing insights from simulations. For instance, this can involve dynamic adjustments to optimise operational efficiency in response to changes in asset utilisation rates. Furthermore, we will explore automated maintenance execution, integrating robotic solutions. However, considerations associated with trust in the DT, safety and human-centric factors need to be addressed. Another future direction could be to extend the framework to enable the development of cognitive twins using semantic technologies such as knowledge graphs. Actionable cognitive twins could enhance the assets' intelligence and enable autonomous activities, leading to more informed decisions.

CRediT authorship contribution statement

Christina Latsou: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dedy Ariansyah:** Data curation, Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – review & editing. **Louis Salome:** Data curation, Formal analysis, Methodology, Software, Validation, Visualization. **John Ahmet Erkoyuncu:** Funding acquisition, Resources, Supervision, Writing – review & editing. **Jim Sibson:** Supervision, Validation. **John Dunville:** Funding acquisition, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Christina Latsou reports financial support was provided by Engineering and Physical Sciences Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This research was funded by the supported by the EPSRC, UK as part of the 'Digital Toolkit for optimisation of operators and technology in manufacturing partnerships' project (DigiTOP; https://digitop.ac.uk; EP/R032718/1), the Centre for Digital Engineering and Manufacturing at Cranfield University and Babcock International. The authors would like to express their special thanks to all management of the Babcock International Company who were working closely with Cranfield University in this project.

Appendix I

Step 1: Defining the DT requirements

Building a DT for the whole system is a complex and iterative task. In this session, the initial approach is to identify the "DTs of the DT or modules of the DT" that include models, software and system representation that make up the whole DT system.

1. What are the parts or processes that the DT is built for? List all the DTs to be created or improved that build up a whole DT system
2. For each DT, what are the expected function and improvement from having a DT?
3. How does DT change the way its physical counterpart operates that leads to measurable benefits?
4. What interface(s) does the DT have considering other DT(s)?

DT requirement template

No.	DT modules	Expected function	Expected improvement	New capability enabled by DT	Interface to different DT systems
1.	Compressor motor state (CMS)	Monitor the compressor motor operation states	Optimise the compressor motor operational duty cycle	Operating hours maintenance schedule	CMP, CCSS, CCSP

(*continued on next page*)

(*continued*)

DT requirement template					
No.	DT modules	Expected function	Expected improvement	New capability enabled by DT	Interface to different DT systems
2.	Compressor motor performance (CMP)	Monitor the performance of the compressor state	Optimise the life consumption of the motor	Condition-based maintenance schedule and fault detection	CMS, CCSS, CCSP
3.	Compressor control system state (CCSS)	Monitor the compressor control system operating states, detect and check if faults are fixed	Improve the availability of the compressor system and process efficiency	Better understanding of the facility's operation Enhanced decision making through prompt detection of faults Capturing and sharing knowledge	CMS, CMP, CCSP
4.	Compressor control system performance (CCSP)	Monitor the performance of the compressor system	Understand the life consumption of system	Condition-based maintenance schedule and fault detection	CMS, CMP, CCSS

Step 2: Determining the DT data and models

Part 1 – DT Data

DT is the 'data-breathed system' whereby it co-live and co-evolve with its physical twin. It relies on the data coming from sensor, software and human input to keep track of the operation and the action performed on the physical asset.

1. For each DT defined in the previous workshop, what data needed to serve the purpose of the DT?
2. What are the constraints encountered when developing DT?
3. What are the data sources, where the data are stored and how to access them?
4. How to link different data types?

Type of data needed (key data categories)	Data constraint	Data sources	Data storage	Data interfaces (linked data type)
Compressor Operation and State	Data Accuracy, lag time of data	PLC Controller	Mindsphere	CSV File, API
Compressor Health Condition	Data Accuracy, lag time of data	Air quantity and temperature sensors	Mindsphere	CSV File, API
Motor Health Condition	Data Accuracy, lag time of data	Electric power and temperature sensors	Mindsphere	CSV File, API

Part 2 – DT models

1. What models required to process the data and how the models are obtained?
2. Where the models are stored and what are the interfaces to link different models?

Compressor Control system —process				
Models needed (key models categories)	**Model constraint**	**Model sources**	**Model storage**	**Model interfaces**
Operating state logic	Precision, accuracy, lag time of data	Agent-based modelling	AnyLogic	Microsoft Excel
Fault detection & repair logic	Precision, accuracy, lag time of data	Agent-based modelling	AnyLogic	Microsoft Excel

Step 3: Determining the desired DT insights

In this stage, DT should have run properly and continuously exchanging the data with the real asset in which the operational changes occur in either side is reflected in its twin. The first part of this session aims at deriving the value from the DT to ensure its purpose is achieved.

1. What are the insights desired from the DT and the data requirement?
2. What types of data analysis required to gain insights from the DT?
3. What are the tools or software used to perform data analysis?

Compressor Control system — process			
Type of data(see data template)	**Desired insight(s) from the DT (intended impact) associated with the type(s) of data**	**Type of data analysis(manual, semi-automatic, automatic)**	**Tools/software for data analysis**
On Load Hours **Operating Hours** **Ready Hours** **Air Quantity** **Final Temperature** **Line Pressure** **Electric Power**	Operational utilisation Compressor faults	automatic	AnyLogic

Step 4: Building the DT user interface

The second part identify the suitable virtual representation to ensure that DT provides an accurate view of the real asset that is easily understood and operated by the users.

1. How the DT information (data and result of analysis) is visualised?
2. How the visualisation varies with different stakeholders?

Compressor Control system — process		
Data type(see data template)	**Stakeholders**	**Visualisation of DT(e.g., Dashboard, VR, AR)**
On Load Hours	Operator	Dashboard
Operating Hours	Facility Manager	Dashboard
Ready Hours		
Air Quantity		
Final Temperature		
Line Pressure		

Step 5: Developing the DT actions

The second part of the session determines the actions (i.e. decisions) that need to be in place to realise the benefits of the DT.

1. What actions need to be executed for each identified condition?
2. How the action is implemented and who is responsible?

Compressor Control system – process			
Insight from DT (see analysis template)	**Condition-action rules**	**Mechanism of action**	**Person in charge**
Fault diagnosis: increase in the temperature due to air cooler blockage	If (T >= 95 °C) replace the cooler	Manual	Operator
Fault diagnosis: machine too warm; identified by the thermostat	If (T >= 100 °C) replace the thermostat	Manual	Operator

Step 6: Building the DT communication network

To achieve smooth synchronisation between physical asset and the DT, the seamless, real-time and bi-directional communication must be established. This template will identify the network communication requirement to ensure fluid and secure connection between physical asset and the DT.

1. How the data is transmitted between physical asset and the DT and what is the communication protocol?
2. How large is the network coverage area and what are the required bandwidth and latency?
3. What are the measures required to ensure network security?

Compressor Control system — process			
Data type (see data template)	Communication technology and protocol	Bandwidth, latency, coverage	Measures for network security
On Load Hours	Communication Link: Internet WAN and wireless LAN	Bandwidth, latency and coverage suitable for design intent	WPA2, firewall, MAC, authentication
Operating Hours	Communication architecture: RESTful system		
Ready Hours	Communication protocol: HTTP		
Air Quantity			
Final Temperature			
Line Pressure			
Electric Power			

Appendix II

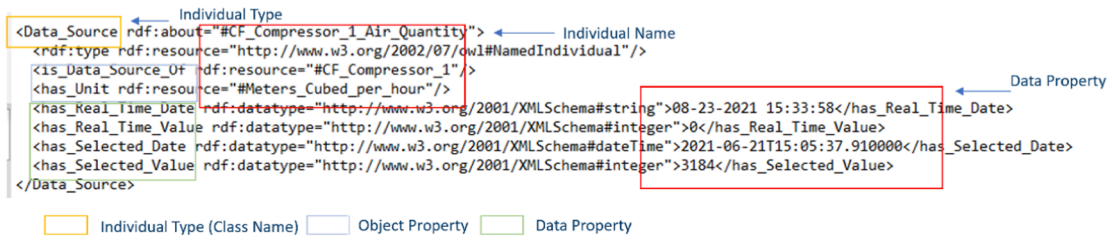


Fig. A1. Sample of data structure in OWL format.

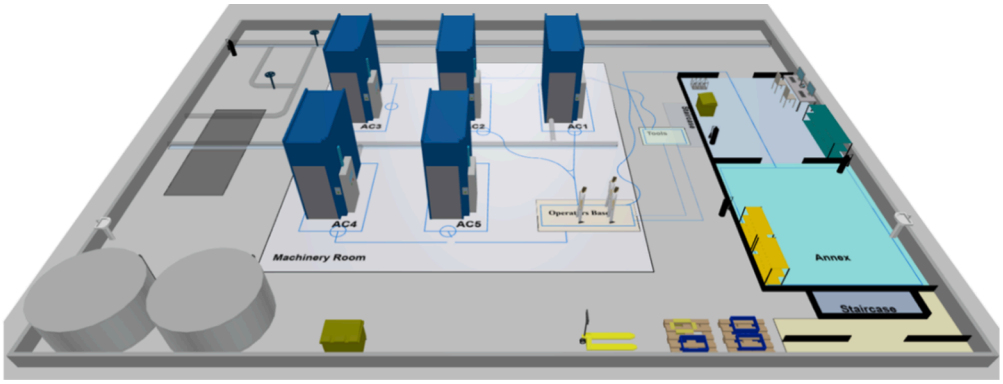


Fig. A2. AnyLogic 3D representation of the compressor station within the industrial facility's shop floor layout.

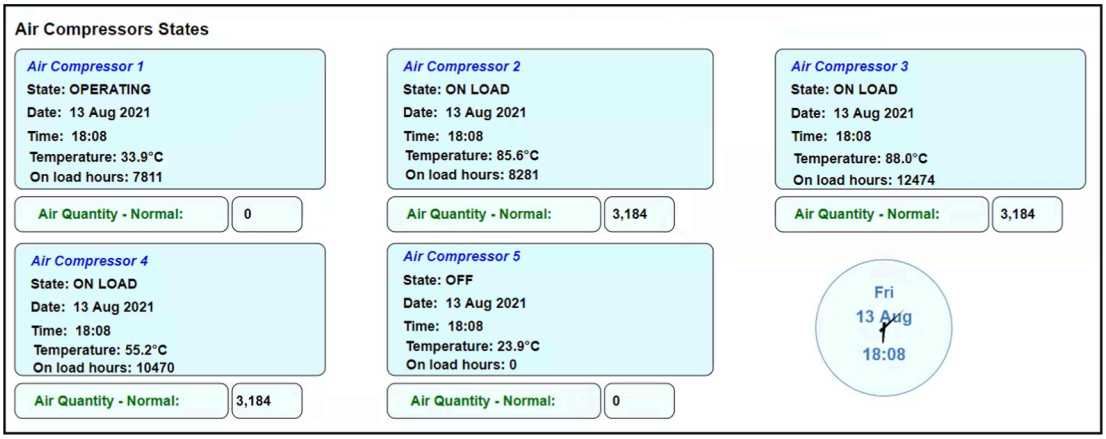


Fig. A3. AnyLogic simulation results for asset monitoring (state, demand and availability of the five compressors).

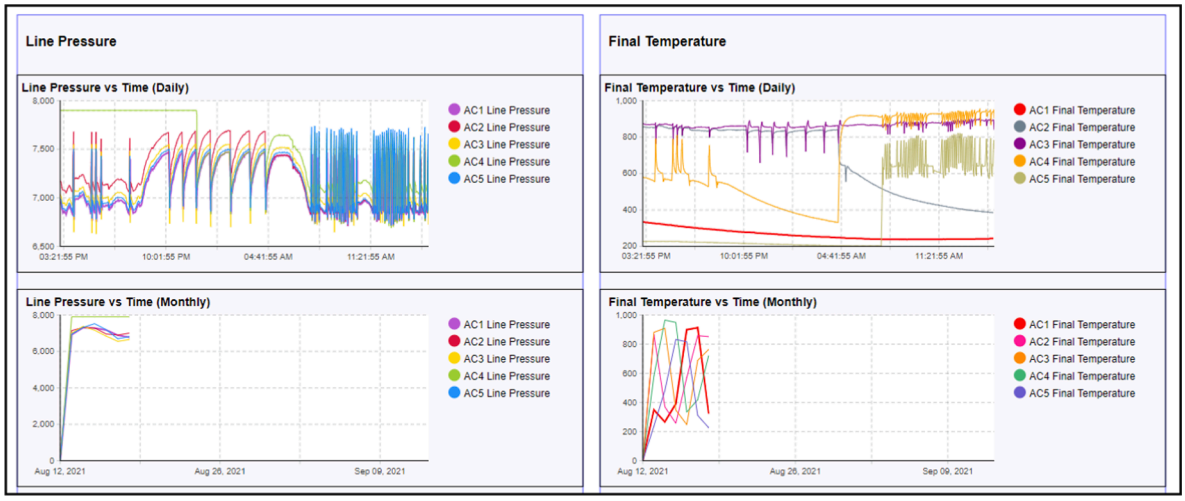


Fig. A4. AnyLogic simulation results for monitoring the daily and monthly line pressure and final temperature of the five compressors.

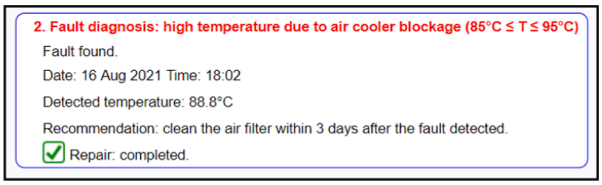


Fig. A5. AnyLogic simulation results for asset fault detection (fault type and condition and repair action of compressor AC2).

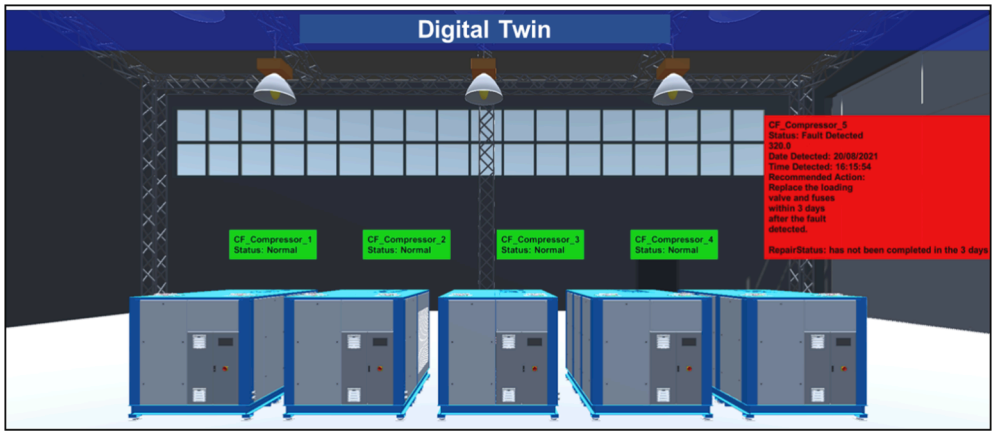


Fig. A6. DT visualisation: User interface for asset fault detection (fault type and condition and repair action of the five compressors).

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2024-10-01
Elsevier
https://doi.org/10.1016/j.aei.2024.102567
Latsou C, Ariansyah D, Salome L,et al., (2024) A unified framework for digital twin development in manufacturing. Advanced Engineering Informatics, Volume 62, Part A, October 2024, Article number 102567

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