Digital Twins: Benefits, Applications and Development Process

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Abstract. Digital twin technology has gained considerable traction in recent years, with diverse applications spanning multiple sectors. However, due to the inherent complexity and substantial costs associated with constructing digital twins, systematic development methodologies are essential for fully capitalizing on their benefits. Therefore, this paper firstly provides an exhaustive synthesis of related literature, highlighting: (1) ten core advantages of implementing digital twin technology; (2) five primary domains in which digital twin applications have been prevalently employed; and (3) ten principal objectives of digital twin applications. Subsequently, we propose a seven-step digital twin application development process, encompassing: (i) Digital Twin Purposing; (ii) Digital Twin Scoping; (iii) Physical Twin Modeling; (iv) Calibration and Validation; (v) Application Logic Development; (vi) External System Integration; and (vii) Deployment and Operation. This structured approach aims to demystify the intrinsic complexity of twinned systems, ensuring that the deployment of digital twin-based solutions effectively addresses the target problem while maximizing the derived benefits.

Keywords: Digital twin · Physical twin · Twinning · Applications · Benefit · Purpose · Development process

1 Introduction

The concept of a digital twin is not new. The underpinning idea was first introduced in David Gelernter's book Mirror Worlds in 1991 [1]. However, it is first two decades later, at a Society of Manufacturing Engineers conference in Troy, Michigan, in 2002, that Dr. Michael Grieves is credited with first publicly introducing the concept [2]. However, even though the concept emerged as early as 2002, the first practical definition is considered to originate from NASA, ten years later, in an attempt to improve the physical-model simulation of spacecraft, defined it as: "*A Digital Twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin* "[3].

Despite its early emergence in the 1990s and subsequent evolution throughout the 2000s, it is essential to understand the fundamental concept of a digital twin and what

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problems it can help to solve before delving into the development of digital twin applications. In recent literature, the digital twin concept has evolved to be generally understood as a digital representation of a real-world object, process, or system [4]. The real-world counterpart of a digital twin is referred to as its physical twin. Examples of physical twins include jet engines, wind turbines, buildings, factories, and cities. The purpose of a digital twin is to serve as an indistinguishable digital representation that accurately reflects its physical twin's observed structure, state, and behavior at a specified fidelity and frequency. Hence, a digital twin simulates the resulting state of the movements, forces, environment-to-system, and system-to-system interactions that the physical twin experience in the physical world.

The development of digital twin applications is generally motivated by the purpose of helping solve problems that are currently underserved by existing technologies. The problems that digital twin applications typically can help to solve involve some level of reflection over a physical twin's past, current, and future states. Such problems typically relate to performance monitoring, process optimization, system maintenance, state estimation, scenario analysis, and similar purposes. Digital twins are, therefore, often used to model, understand, and analyze complex systems where the system's performance, reliability, and safety concerns are critical. In a digital twin application, a physical twin is being observed in the physical world by instrumenting its environment with various sensors that collect data about different operation aspects, such as temperature, pressure, vibration, duration, acceleration, velocity, weight, and more, as illustrated in Fig. 1. This data is then used to update the digital twin's model of the physical twin. The digital twin application can store the collected data for keeping a historical record, use it to reflect upon the current and future state of the physical twin, and intervene in the operation of the physical twin if necessary.

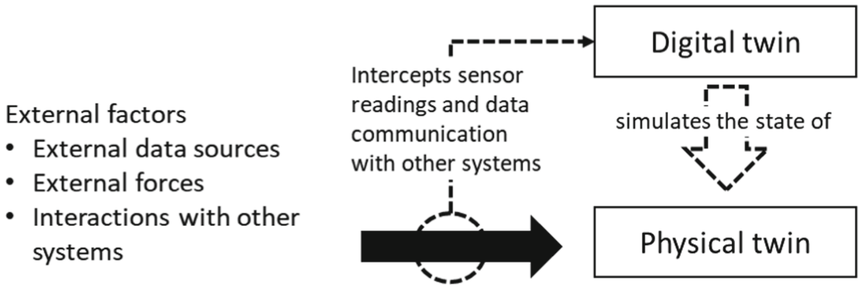

Fig. 1. Conceptual model of the relation between a digital twin and its physical twin.

Due to the intrinsic complexity of the systems being twinned, the twinning process is a costly undertaking requiring significant effort and time. To ensure this effort is worthwhile the benefits of applying a digital twin-based approach to the problem at hand must be properly investigated and understood. Hence, there is a need for establishing systematic development methodologies before the benefits of adopting digital twin-based applications can be fully explored across the different sectors of society.

In this paper, we first review the benefits of digital twins and their applications in different domains, and then we address the unmet challenges of providing a best practice development methodology for digital twin applications [4], by outlining the steps of a development process that have successfully applied across several application domains.

2 Benefits of Digital Twins

Many companies have started to create digital twins for their products, processes, and systems because of the many benefits digital twins are promised to provide. Data collected from existing products and production processes allow digital twins to effectively identify systemic deficiencies, optimize processes, improve quality, and reduce cost. Furthermore, a digital twin can use the same data to lower the environmental footprint and production cost by co-optimizing the design of the following product generation together with its production processes. In the virtual environment provided by digital twins, engineers can effectively simulate real-world conditions, analyze what-if scenarios under any circumstances imaginable, and visualize the outcomes. Hence, digital twins help engineers to analyze and predict a physical twin's performance under different operation conditions. As a result of this, helps engineers to understand the past, view present conditions, and prevent future problems. In short, digital twinning provide improved situation awareness, optimizes decision-making, supports planning, and effective implementation of actions. Based on the statements in the literature, ten primary benefits associated with the implementation of digital twin technology can be summarized:

Efficiency enhancements: Digital twin frameworks can substantially reduce the effort required to perform specific tasks, with up to 50% reduction in certain cases [5]. Moreover, they contribute to a decrease in downtime for manufacturing systems. For instance, employing digital twins for grinding wheels results in a 14.4% increase in energy and resource efficiency, thus promoting sustainable manufacturing processes [6].

Increased adaptability: Digital twins facilitate small size production, catering to individual customer needs and requirements [7]. Furthermore, they enable shorter production cycles through the implementation of smart manufacturing systems, resulting in agile and efficient operations [8].

Superior scheduling and decision-making: The bi-level dynamic scheduling architecture, based on service unit digital twin agents, promotes more effective scheduling practices [9]. By providing real-time monitoring, simulation, and decision-aid systems, digital twins support production operations, predictive maintenance, and strategic planning initiatives [10, 11].

Process optimization and resource management: The integration of digital twin technology within remanufacturing processes leads to optimization and improvements in resource recycling [6, 10]. Additionally, digital twins streamline inventory management within physical internet hubs, enhancing operational efficiency [12].

Autonomous manufacturing capabilities: Digital twin frameworks, such as data– and knowledge-driven models for digital twin manufacturing cells, foster intelligent perception, simulation, understanding, prediction, optimization, and control strategies that support autonomous manufacturing processes [13].

Advanced monitoring and control: Digital twins enable real-time monitoring of maintenance, product quality, resource utilization, and overall efficiency [14]. Consequently, this technology contributes to improved fleet management [15] and smart building management practices [16].

Competitive edge and innovation: The adoption of digital twins equips enterprises with innovative technologies that bolster their market position, enhance product quality, and improve operational efficiency [8, 17].

Sophisticated simulation and training: The use of digital twins in generating realistic simulations for training purposes enriches the learning experience and reduces associated costs, thereby offering a more effective approach to skill development [18].

Secure and reliable data management: The integration of blockchain technology within digital twin systems ensures robust data integrity and security, safeguarding valuable information across various industries [19, 20].

Customized production and sustainable business models: Combining digital twins, blockchain, and additive manufacturing empowers organizations to adopt a customer-centric production paradigm [19]. The utilization of digital twin platform networks enables the development of sustainable business models that encompass economic, social, and environmental benefits [6, 7, 17].

3 Digital Twin Applications

Digital twin technology has experienced rapid adoption across a diverse range of industries, transforming processes and systems with innovative, data-driven solutions. The domains which have popularly applied digital twin technology are manufacturing, energy, buildings, smart cities, logistics and supply chains.

In manufacturing, digital twin technology has been applied across various sub-domains, e.g., equipment design [21], manufacturing resource recommendation [22], personalized production [19], manufacturing processes [23], and additive manufacturing [24]. Digital twins are employed for purposes of monitoring [25], simulation [26], analysis [27], control [28], optimization [21], defect detection [7], automation [29], and continuous improvement [26]. They play a crucial role in Industry 4.0 development, contributing to robustness, resilience, self-adaptation, real-time analysis, and product detection.

In the energy sector, digital twin technology has been applied, e.g., electricity distribution networks [30], planning [31], and consumption management [32], etc. Digital twins have been applied to enhance the efficiency [33], optimization [34] and control [35], facilitate monitoring [32], prediction [36], device health maintenance [30], real-time interaction [31], co-simulation and system performance validation [37].

In the building industry, Digital twin technology provides innovative solutions across various sub-domains. It helps stakeholders make better decisions, improve building performance, and facilitate efficient management of building assets. Applications include building embodied carbon estimation [38], building automation, energy efficiency and occupant comfort [39], and building maintenance [40].

In smart cities, digital twin technology has been applied across various sub-domains, including infrastructure [41], healthcare services [42], urban landscape management

[43], and facility venue management [44]. Each sub-domain leverages digital twins for specific purposes, e.g., monitoring [45], prediction, optimization and control [41], data analysis [42], visualization [43], security [46], and policy development [41], contributing to more efficient, sustainable, and livable urban environments.

Furthermore, digital twin technology has made significant strides in logistics and supply chains, enabling new approaches to monitoring, control, integration, and optimization. These advancements have improved the resilience, efficiency, and sustainability of various sub-domains. Applications include supply chain control [47], production logistics [48], city logistics [45], and supply chain optimization [49].

4 Digital Twin Application Development

A digital twin application is, in essence, a software system that uses real-world data and digital models to predict how a physical twin will perform. To do so, it integrates IoT, Big Data, and AI technologies. IoT and Big Data technologies are used for collecting relevant data about the physical twin's operational environment, and AI technologies are used to analyze the current and predict the future states of the physical twin. The choice of specific technologies depends on the application domain where the digital twin will be used.

A conceptual architectural model of a digital twin application with its constituent elements is shown in Fig. 2. These constituent elements form a recurring architectural pattern that can be observed for the development of digital twin applications across multiple domains.

The development of digital twin applications is a complex and multi-disciplinary effort, involving experts from multiple fields, including engineering, computer science, data science, and domain-specific experts. To support the effective development of digital twin applications the development process has to be divided into a number of steps. The decomposition of the development process into separate steps can be done in different ways and will typically reflect the methodologies of the engineering disciplines taking part in the digital twin development. Based on the authors' observations from several industrial digital twin R&D projects [50, 51], mechanical engineers, data scientists, and software engineers have different perspectives on how to decompose the development of a digital twin. The steps proposed in this paper are based on the authors' practical experience from these R&D projects and are illustrated in Fig. 3.

Digital twin purposing: The first thing to address when starting a digital twin development project is to clearly define the purpose of the digital twin application. What unmet need will the digital twin application fulfill, that cannot simply be fulfilled by using existing technologies. Is a digital twin the right solution; that is, is a digital replica of the physical twin essential to solve the problem at hand. What additional benefits does a digital twin bring that cannot be achieved by existing technologies. How are these benefits assessed and evaluated, and will the expected benefits justify the development cost. First when these concerns have been considered a digital twin development project should be initiated.

Digital twin scoping: The next step is to determine the scope of the digital twin. The scope is defined by the boundary of the real-world object, process, or system being

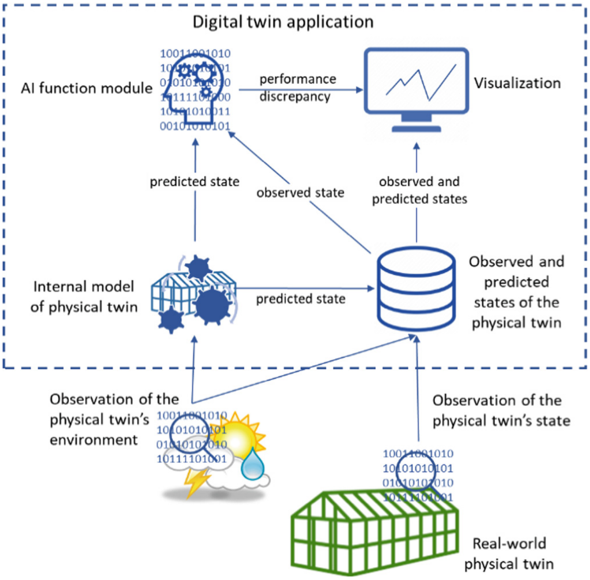

Fig. 2. Example of a digital twin application for continuous energy performance monitoring of a commercial greenhouse.

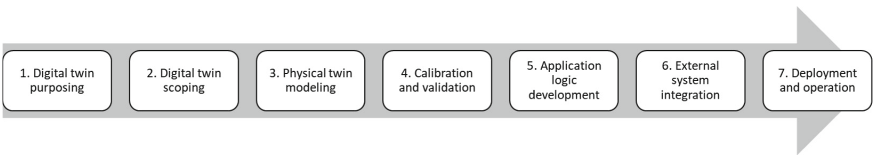

Fig. 3. Steps in the development of digital twin applications.

twinned, and the purpose of developing the digital twin application. Ignoring the importance of correct scoping may lead to undersized or oversized digital twins. That is, the digital twin level of details does not match the required model fidelity for the problem at hand. For instance, if the purpose is to predict the remaining lifetime of a single fan in a building's ventilation system, the scope is defined by the boundary of the mechanic fan and the process parameters affecting the fan's operation conditions. It is therefore not necessary to do detailed twinning of the whole building to meet the purpose of the digital twin application. Due to the natural boundaries of the real-world object, process, or system being twinned, digital twins typically materialize at one of three levels: component, unit, and system. Each of these levels is described in Table 1 based on their general definitions in dictionaries of the English language.

Depending on the application, digital twins can be created as hierarchical architectures that a higher-level digital twin is created by composing digital twins at the lower level, or they can be constructed as monolithic architecture at the respective level.

Table 1. Scope of digital twins.

Component	A component is a constituting functional part or element of a larger whole, especially a part of a machine or vehicle. For example, the fan in a ventilator unit or a joint in a robot arm
Unit	A unit is a single whole part of a system. For example, the ventilator unit in a building's ventilation system or a single robot in a manufacturing production line
System	A system is a group of interacting or interrelated elements that act according to a set of rules to form a unified whole. Hence, a system defines a way of working, organizing, or doing something which follows a fixed plan or set of rules. A system, surrounded and influenced by its environment, is described by its boundaries, structure and purpose and is expressed in its functioning. For example, the ventilation system in a building or a manufacturing production line

Physical twin modeling: This step focuses on creating the digital twin's internal model of the physical twin. The internal model captures the behavior, attributes, and relationships of the physical twin. This model can either be created using a specification-driven or data-driven approach. A specification-driven approach uses relevant design specifications to create a white–or grey-box model of the physical twin, whereas a data-driven approach creates a black-box model based on historical data collected from the physical twin and its environment. White–and grey-box modeling require detailed design specifications of the physical twin, whereas black-box modeling requires big data for the external factors influencing the physical twin and the behavioral response of the physical twin to these external factors. Depending on the application domain such big data can be a large dataset for the production cycles of a product in a manufacturing line, or it can be a large dataset spanning multiple years of data collection, in the case where the behavior of the physical twin depends on external factors such as seasonal weather changes. The latter is for instance the case for digital twins of wind turbines [52], photovoltaic [53], buildings [51], and greenhouses [54–56]. White–and grey-box modeling is typically used when the available data for a physical twin is insufficient to create a black-box model, and black-box modeling is used when the available design specifications are insufficient but there is sufficient data. Deciding on the modeling approach; white box, grey box, or black box, depends on what design specifications and data are and will be available. Making this decision requires identifying the information and data sources, including sensors, control systems, and other sources of information, available for creating the digital twin's internal model of the physical twin. It is the authors' experience that stakeholders often overestimate what design specification and data they have. Hence, the choice of modeling method should not be prematurely decided before the availability of design specifications and data have been properly investigated.

Calibration and validation: The digital twin must be calibrated and validated to ensure that it accurately represents the behavior of the physical twin. Calibration is the process of fine-tuning the digital twin's model parameters to closely match the behavior of the physical twin. It involves adjusting the parameters within the model based on the data collected from the physical twin and its environment. For example, if the digital twin of a greenhouse predicts its energy consumption to be higher than the actual consumption, the model parameters need to be adjusted to better align with the real-world data. This process may require multiple iterations to achieve a satisfactory level of accuracy. After the calibration process, validation is carried out to ensure that the digital twin's model can accurately predict the behavior of the physical twin under various conditions. Validation is done by comparing the digital twin's predictions to independent real-world data that was not used during the calibration process. If the model's predictions closely align with the actual performance of the physical twin, it is considered to be a valid representation of the physical twin.

Application logic development: Developing the logic of a digital twin application requires the creation of an AI function module that encapsulates the application logic required to fulfill its intended purpose. The AI function module leverages the internal digital model of the physical twin, which serves as the foundation for implementing various AI methods. These methods can include statistical analysis, machine learning, deep learning, or agent-based simulation, among others [57]. The selection of an appropriate AI method for implementing the AI function module depends on the specific purpose of the digital twin's development. Different applications may benefit from distinct state-of-the-art methodologies that are best suited to address special challenges and requirements of their use cases. For instance, a digital twin developed for predictive maintenance might employ machine learning algorithms to identify patterns and anomalies in the sensor data, thereby enabling the early detection of potential equipment failures. On the other hand, a digital twin for simulating the effect of electric vehicle charging on the stability of the electricity grid will benefit from agent-based simulation, wherein individual agents represent diverse entities that interact and adapt according to a set of predefined rules. Moreover, it is essential to consider the type and volume of data available for training and validation when selecting an appropriate AI method for the AI function module. While some approaches may require large datasets to deliver accurate predictions, others might be more suitable for scenarios with limited data availability or noisy data. In addition to the AI function module, most digital twin applications include a visualization component that shows relevant information about the physical twin's historical, current, and predicted future state. This visualization component provides actionable insights and supports decision-making.

External system integration: To achieve a successful integration of the digital twin application in its deployment environment, it is important to comply with de jure and de facto standards that can ensure interoperability between the digital twin and existing systems, such as PLC (Programmable Logic Controller), SCADA systems (Supervisory control and data acquisition), IoT and Cloud platforms. These standards facilitate consistent data exchange and communication protocols, enabling the digital twin to access and process real-time data from diverse sources without compatibility issues. Such standards can be industry-specific or based on general-purpose protocols, such as OPC UA (Open Platform Communications Unified Architecture) and MQTT (Message Queuing Telemetry Transport), which are widely employed in the Internet of Things (IoT) domain.

Deployment and operation: Once a digital twin has been created and deployed in an application, it must be continuously monitored and validated to ensure that it remains accurate. Continuous validation is required as the physical twin may change, such as wear and tear, modifications, replacements of components, or updates of its control logic. These alterations can impact the system's performance and behavior, rendering the digital twin's current model of the physical twin potentially outdated. It is therefore necessary to regularly assess the digital twin's accuracy in representing the physical twin, taking into account any changes that have occurred. When discrepancies are identified, the digital twin's model parameters and algorithms must be updated to reflect the new state of the physical twin.

5 Conclusions

The use of digital twins provides promising benefits in many application domains. Digital twins enable better planning, decision-making, and situation awareness by modeling and analyzing the past, present, and future states of physical systems across various industries, such as manufacturing, energy, buildings, smart cities, and logistics. Still, being an emerging technology, its successful adoption requires the development of methodologies that enable best practices of architectural principles and software technological advances to be shared across domains. This paper presented a conceptual architectural model and development process based on the authors' own experience from various industrial R&D projects. Future work will explore the architectural model and development process in greater detail to identify commonalities and variabilities related to the application of digital twins in different domains.

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References

1. Gelernter, D.: Mirror worlds—or the day software puts the universe in a shoehox. (1991)
2. Grieves, M.W.: Virtually intelligent product systems: digital and physical twins. In: Complex systems engineering: theory and practice, pp. 175–200. American Institute of Aeronautics and Astronautics, Inc (2002)
3. Glaessgen, E., Stargel, D.: The digital twin paradigm for future NASA and US Air Force vehicles. In: 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 2012
4. Semeraro, C., et al.: Digital twin paradigm: A systematic literature review. Comput. Ind. **130**, 103469 (2021)
5. Lehner, D., et al.: AML4DT: A model-driven framework for developing and maintaining digital twins with automation ML. In: 2021 26th IEEE international conference on emerging technologies and factory automation (ETFA). pp. 1–8 (2021)

6. Kannan, K., Arunachalam, N.: A digital twin for grinding wheel: an information sharing platform for sustainable grinding process. J. Manuf. Sci. Eng.-Trans. ASME **141**, 14 (2019)
7. Warke, V., et al.: Sustainable development of smart manufacturing driven by the digital twin framework: a statistical analysis. Sustainability **13**, 49 (2021)
8. Mudassar, R., et al.: Digital twin-based smart manufacturing system for project-based organizations: A conceptual framework. In: Proceedings of international conference on computers and industrial engineering, CIE. Wuhan, China (2019)
9. Zhang, J., et al.: Bi-level dynamic scheduling architecture based on service unit digital twin agents. J. Manuf. Syst. **60**, 59–79 (2021)
10. Lim, K.Y.H., et al.: Digital twin architecture and development trends on manufacturing topologies. In: Intelligent systems reference library, pp. 259–286. Singapore (2021)
11. Süve, M.F., et al.: Predictive maintenance framework for production environments using digital twin. In: Lecture notes in networks and systems. Istanbul, Turkey (2022)
12. Leung, E.K.H., Lee, C.K.H., Ouyang, Z.: From traditional warehouses to Physical Internet hubs: A digital twin-based inbound synchronization framework for PI-order management. Int. J. Prod. Econ., **244**, (2022)
13. Zhang, C., et al.: A data- and knowledge-driven framework for digital twin manufacturing cell. In: 11th CIRP conference on industrial product-service systems. Elsevier, Xian, Peoples R China (2019)
14. Rafsanjani, H.N., Nabizadeh, A.H.: Towards digital architecture, engineering, and construction (AEC) industry through virtual design and construction (VDC) and digital twin. Energy Built Environ., (2021)
15. Renaud, G., Liao, M., Bombardier, Y.: Demonstration of an airframe digital twin framework using a CF-188 full-scale component test. Lect. Notes Mech. Eng., 176–186 (2020)
16. Chevallier, Z., Finance, B., Boulakia, B.C.: A reference architecture for smart building digital twin. In: CEUR workshop proceedings. Nanterre, France (2020)
17. Li, X., et al.: Sustainable business model based on digital twin platform network: the inspiration from Haier's case study in China. Sustainability **12**, 26 (2020)
18. Camacho, F.D., et al.: Validation through a digital twin of a Stewart platform with irregular geometry with 6 DOF for simulation of a transport vehicle. In: 16th IEEE international conference on automation science and engineering (CASE). IEEE, Sangolqui, Ecuador (2020)
19. Guo, D.Q., et al.: A framework for personalized production based on digital twin, blockchain and additive manufacturing in the context of Industry 4.0. In: 16th IEEE international conference on automation science and engineering (CASE). IEEE, Guangdong, Peoples R China (2020)
20. Khan, A., et al.: Toward smart manufacturing using spiral digital twin framework and twinchain. IEEE Trans. Industr. Inf. **18**, 1359–1366 (2022)
21. Mourtzis, D., et al.: Equipment design optimization based on digital twin under the framework of zero-defect manufacturing. In: 2nd international conference on industry 4.0 and smart manufacturing (ISM). Elsevier Science Bv, Rion, Greece (2020)
22. Li, X.X., et al.: Framework for manufacturing-tasks semantic modelling and manufacturing-resource recommendation for digital twin shop-floor. J. Manuf. Syst. **58**, 281–292 (2021)
23. Deac, G.C., et al.: Machine vision inmanufacturing processes and the digital twin ofmanufacturing architectures. In: Annals of DAAAM and proceedings of the international daaam symposium. (2017)
24. Scime, L., Singh, A., Paquit, V.: A scalable digital platform for the use of digital twins in additive manufacturing. Manuf. Lett., (2021)
25. Qamsane, Y., et al.: A unified digital twin framework for real-time monitoring and evaluation of smart manufacturing systems. In: 15th IEEE international conference on automation science and engineering (IEEE CASE). IEEE, USA (2019)

26. Friederich, J., et al.: A framework for data-driven digital twins for smart manufacturing. Comput. Ind., **136**, (2022)
27. Gopalakrishnan, S., Hartman, N.W., Sangid, M.D.: Model-based feature information network (MFIN): A digital twin framework to integrate location-specific material behavior within component design, manufacturing, and performance analysis. Integr. Mater. Manuf. Innov. **9**, 394–409 (2020)
28. Nie, Q.W., et al.: A multi-agent and internet of things framework of digital twin for optimized manufacturing control. Int. J. Comput. Integr. Manuf., 22
29. Göppert, A., et al.: Pipeline for ontology-based modeling and automated deployment of digital twins for planning and control of manufacturing systems. J. Intell. Manuf., (2021)
30. Zhang, G., et al.: An architecture based on digital twins for smart power distribution system. In: 2020 3rd international conference on artificial intelligence and big data (ICAIBD). pp. 29–33 (2020)
31. Niu, W., et al.: Power grid planning framework and application prospects based on digital twin. In: The 10th renewable power generation conference (RPG 2021). pp. 672–677 (2021)
32. Zhang, M., et al.: Equipment energy consumption management in digital twin shop-floor: a framework and potential applications. In: 15th IEEE international conference on networking, sensing and control (ICNSC). IEEE, Beijing, Peoples R China (2018)
33. Aliyu, H.O., et al.: Digital twin framework for holistic and prognostic analysis of the Nigerian electricity supply industry: A proposal. In: 5th IEEE annual international conference on information communications technology and society (ICTAS). IEEE, Minna, Nigeria (2021)
34. Yu, Q., et al.: Research of digital twin in power system optimization-take offshore platform for example. In: IET conference publications. Beijing, China (2020)
35. Wu, J., et al.: Research and design of a digital twin-based enterprise architecture digital control platform for provincial electrical power company. In: 2021 6th international conference on control, robotics and cybernetics (CRC). (2021)
36. Zhang, H., et al.: Hybrid data-physics based digital twin modeling framework for the power system of bobsleigh and tobogganing venue for Beijing winter Olympics. In: 2021 6th international conference on power and renewable energy (ICPRE). (2021)
37. Perabo, F., et al.: Digital twin modelling of ship power and propulsion systems: application of the open simulation platform (OSP). In: IEEE 29th international symposium on industrial electronics (ISIE). IEEE, Trondheim, Norway (2020)
38. Chen, C., et al.: A conceptual framework for estimating building embodied carbon based on digital twin technology and life cycle assessment. Sustainability **13**, (2021)
39. Clausen, A., et al.: A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings. Energy Inform., **4**, (2021)
40. Wang, W., et al.: Digital twin-based framework for green building maintenance system. In: 2020 IEEE international conference on industrial engineering and engineering management (IEEM). pp. 1301–1305 (2020)
41. Raes, L., et al.: DUET: A framework for building secure and trusted digital twins of smart cities. IEEE Internet Comput., 1 (2021)
42. Laamarti, F., et al.: An ISO/IEEE 11073 standardized digital twin framework for health and well-being in smart cities. IEEE Access **8**, 105950–105961 (2020)
43. Ruohomaki, T., et al.: Smart city platform enabling digital twin. In: 9th international conference on intelligent systems (IS), pp. 155–161. IEEE, Helsinki, Finland (2018)
44. Meta, I., et al.: The camp nou stadium as a testbed for city physiology: a modular framework for urban digital twins. Complexity, **2021**. (2021)
45. Belfadel, A., et al.: Towards a digital twin framework for adaptive last mile city logistics. In: 2021 6th international conference on smart and sustainable technologies (SpliTech). pp. 1–6 (2021)

46. El Azzaoui, A., et al.: Blockchain-based secure digital twin framework for smart healthy city. Lect. Notes Electr. Eng. **716**, 107–113 (2021)
47. Park, K.T., Son, Y.H., Noh, S.D.: The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. Int. J. Prod. Res. **59**, 5721–5742 (2021)
48. Pan, Y.H., et al.: Digital twin based real-time production logistics synchronization system in a multi-level computing architecture. J. Manuf. Syst. **58**, 246–260 (2021)
49. Marmolejo-Saucedo, J.A.: Digital twin framework for large-scale optimization problems in supply chains: a case of packing problem. Mob. Netw. & Appl., 17
50. Howard, D.A., et al.: Greenhouse industry 4.0—digital twin technology for commercial greenhouses. Energy Inform., **4**(2), 37 (2021)
51. Clausen, A., et al.: A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings. Energy Inform. **4**(2), 40 (2021)
52. Sørensen, J.V., Ma, Z., Jørgensen, B.N.: Potentials of game engines for wind power digital twin development: an investigation of the Unreal Engine. Energy Inform. **5**(4), 39 (2022)
53. Clausen, C.S.B., Ma, Z.G., Jørgensen, B.N.: Can we benefit from game engines to develop digital twins for planning the deployment of photovoltaics? Energy Inform. **5**(4), 42 (2022)
54. Howard, D.A., Ma, Z., Jørgensen, B.N.: Digital twin framework for energy efficient greenhouse industry 4.0. in ambient intelligence—Software and applications. 2021. Springer International Publishing, Cham (2021)
55. Howard, D.A., Ma, Z., Jørgensen, B.N.: A case study of digital twin for greenhouse horticulture production flow. In: 2022 IEEE 2nd international conference on digital twins and parallel intelligence (DTPI). (2022)
56. Howard, D.A., et al.: Data architecture for digital twin of commercial greenhouse production. In: 2020 RIVF international conference on computing and communication technologies (RIVF). (2020)
57. Værbak, M., et al.: Agent-based modelling of demand-side flexibility adoption in reservoir pumping. In: 2019 IEEE sciences and humanities international research conference (SHIRCON). (2019)