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Review

A review of unit level digital twin applications in the manufacturing industry

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ABSTRACT

In recent years, the hype around Digital Twins (DTs) has been exponentially increasing in both industry and academia. DTs are a potential solution to increase automation and advance towards Smart Manufacturing. Manufacturing DTs have been implemented at different hierarchical levels, ranging from system of systems to unit level. Increasing computational capacity and data exchange rates can enable DT implementations for real-time applications. Several literature reviews on manufacturing DTs have been published. However, no previous paper focuses on manufacturing DTs at the unit level for which real-time control is most applicable. Simultaneously, the challenges to engineer DTs with real-time capabilities are enormous, both from a scientific and technological perspective. Therefore, we focus on DTs of single production units such as traditional machine tools, additive manufacturing machines and advanced robotic applications. In this systematic literature review, 96 papers about practical unit level DT applications found in the Scopus database using a combination of the keywords "Digital Twin", "Production" and "Manufacturing" are reviewed. We summarize how DTs are currently implemented and operated, and what potential benefits DTs offer at the unit process level in four categories: generic reference models, services, DT content (models and data) and DT deployment (hardware and software). Following the thematic analysis, an overall discussion, summary of key contributions and identified research gaps, and outlook into future research avenues is given. Key findings of this review can be summarized as: focus on DT components versus being holistic; need to share data and models across multiple stakeholders; lack of physical fidelity of the models; stark contrast of lab scale developments and real world testing, e.g., historical data and storage related challenges; lack of clear definition of DT in industry, and missing semantic interoperability between a wide variety of domains.

Contents

Abbreviations: CAD, Computer Aided Design; CAM, Computer Aided Manufacturing; CNC, Computer Numerical Control; CPS, Cyber-Physical System; DT, Digital Twin; FEM, Finite Element Method; MQTT, Message Queuing Telemetry Transport; NC, Numerical Control; OPC-UA, OPC Unified Architecture; PLC, Programmable Logic Controller; PLM, Product Life Cycle Management; SM, Smart Manufacturing; SQL, Structured Query Language; STL, Standard Tessellation Language; URDF, Unified Robot Description Format; XML, Extensible Markup Language

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Introduction

Four revolutions have been undertaken in the manufacturing industry to optimize the production of different types of goods. The fourth industrial revolution (also called Industry 4.0) focuses on automation with the digitalization of manufacturing operations being the cornerstone. Industry 4.0 is enabled by advances in information technologies such as Cyber-Physical Systems (CPSs), the Industrial Internet of Things, cloud computing, and artificial intelligence [63,106]. These technologies allow manufacturing systems to acquire data from different sensors, and to conduct computations and control locally or in a remote (typically cloud) setting. For using available computing power to its full value, structuring data from the physical manufacturing elements in order for the data to be transferred to a virtual counterpart is sensible. Suppose this virtual counterpart is equipped with predictive power and the ability to command the physical counterpart. In that case, the virtual counterpart can assist with improving the overall performance of manufacturing activities. The union between such virtual counterparts and corresponding physical elements is commonly known as Digital Twins (DTs). Formally, ISO 23247:2021 [58] defines a manufacturing DT as a “fit-for-purpose digital representation of an observable manufacturing element with a means to enable convergence between the element and its digital representation at an appropriate rate of synchronization”.

In a typical manufacturing setting, DTs can be organized into three hierarchical levels as shown in Fig. 1: 1) Unit level, 2) System level, and 3) System of Systems level [120]. Unit level DTs represent the smallest elements in a manufacturing operation, i.e., single production units such as a machine tool capable of performing an activity to manufacture a product. Depending on the application, unit level DTs describe attributes such as geometric appearance, behavior and function of manufacturing equipment, process physics, workpiece properties and tooling [129]. The complexity and comprehensiveness of DTs generally increase from the unit level (most narrow) to more sophisticated DTs of system and system of systems. While system level DTs focus on how systems work as a whole,

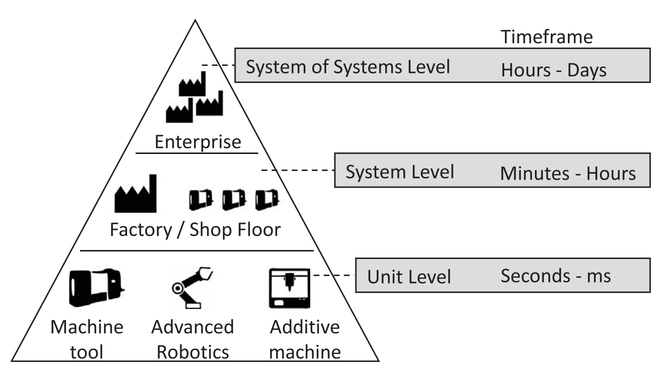


Fig. 1. Hierarchical perspective of DTs for the manufacturing industry. *Timeframe* indicates approximated response times required to provide control feedback at the different hierarchical levels.
Adapted from [129].

Table 1
Related DT reviews and concept papers (title-abs-key("Digital Twin" AND ("Manufacturing" OR "Production")) Scopus, 18–03–2022). Acronyms for labeling the specific focus of papers: Cyber-Physical System (CPS), Product Life Cycle Management (PLM), Smart Manufacturing (SM), Definition (D), Application (A). Key aspects abbreviations used are: Reference model & Concept (RC), Modeling & Simulation (MS), Hardware (H), Software (S).

Review and concept papers	Area	Digital Twin components					Paper Scope			
		R&C	MS	Data	H&S	Services	Factory	Shopfloor	Unit	Product
Rosen et al. [113]	CPS, I4.0	x	x		H		x	x		
Negri et al. [94]	D, CPS, I4.0	x	x		S	x	x	x	x	
Schleich et al. [116]	PLM	x	x		S	x			x	
Tao and Zhang [132]	SM, CPS, A	x	x	x	S	x		x		
Uhlemann et al. [135]	CPS, I4.0, A	x		x	H		x	x		
Kritzinger et al. [66]	D, A, I4.0	x				x	x	x	x	
Tao et al. [128]	CPS, PLM	x		x		x			x	x
Qi and Tao [106]	SM	x		x		x	x	x	x	
Zhuang et al. [154]	SM	x	x	x	H, S	x		x		
Tao et al. [131]	D, A		x	x	H, S	x				x
Cimino et al. [31]	CPS, D, A		x	x	H, S	x		x	x	x
Lu et al. [81]	SM, A	x		x	H	x	x		x	
Errandonea et al. [34]	A					x		x	x	x
Melesse et al. [88]	A					x		x	x	x
Sjarov et al. [121]	D	x								
Zhang et al. [146]	A	x	x		H				x	
Wang et al. [137]	A	x	x	x	H, S	x			x	
Ciano et al. [30]	SM, I4.0, PLM	x								
Jones et al. [61]	D	x				x				
Agnusdei et al. [3]	A	x								
Xie et al. [142]	A, PLM	x	x	x	H, S	x				x
Atalay et al. [11]	A	x				x		x	x	x
He and Bai [47]	A	x				x		x	x	x
Liu et al. [76]	D, A, PLM		x	x		x		x	x	x

combining information of unit level DTs can lead to complex, aggregate DTs for manufacturing shop floors and factories [8,120].

This paper examines the literature on manufacturing DTs at the unit level. The motivation to study unit level DTs is twofold: 1) the need to understand the particular challenges associated with engineering DTs capable of real-time control which is most applicable at the unit level, and 2) the lack of relevant studies on unit level DTs. We categorized the literature along four dimensions summarized in the sections Generic Reference Models for Digital Twins, Digital Twin Services, Digital Twin Content and Digital Twin Deployment. The intention of the categorization is to provide a clear overview for guiding the reader depending upon the reader's main interest. Further, tables structuring the literature support the reader in determining relevant literature to explore in the future.

The paper is organized as follows: The section Related Literature positions and differentiates this research to related review and concept papers. The section Research Methodology describes the methodology for the systematic literature review of manufacturing DTs at the unit level. The section Quantitative analysis provides a numerical overview of selected characteristics of the reviewed papers. Following, the section Review of Unit Level Manufacturing Digital Twins presents the results of the literature review. The section Discussions and Conclusions states the limitations and the main findings of this literature review.

Related literature

This section positions and differentiates our literature review from recent related research on manufacturing DTs. Table 1 summarizes 24 manufacturing DT review and concept papers from 2015 to 2021. Note, that we did not provide a comprehensive overview of all publications reviewing manufacturing DTs. Instead, we focused on a fraction of reviews with a citation count above 100. In the following paragraphs, we summarized the content of these papers. Then, we differentiated their contributions from the contributions of our work.

The first research stream focuses on conceptualizing CPS-based DTs. Rosen et al. [113] demonstrated how DTs facilitate closing the "life cycle loop" and increase autonomy in manufacturing systems at the example of a CPS consisting of four production units. Negri et al. [94] reviewed definitions and applications of CPS-based DTs and introduced a simulation-based concept that relies on a semantic metadata model of the CPS. Uhlemann et al. [135] presented a multi-modal data acquisition approach, describe the composition of a database, and provided guidelines for implementing CPS-based DTs. Kritzinger et al. [66] classified existing DTs by the level of data integration between a physical and virtual entity. They stated that most DT research has a low integration, i.e, they are just a model or only have uni-directional communication, while the majority of "real" DTs focus on scheduling and production planning. The use of DTs in CPS is still evolving and requires more research to fully integrate DTs into CPS and realize their potential for autonomous systems. One of the challenges of integrating DTs into CPS is the need to develop a comprehensive semantic metadata model that can capture the complex interactions between physical and computational components. Another challenge is the need to develop robust data acquisition and processing techniques to ensure that the DTs are accurate and up to date.

A second research stream relates to PLM and DTs. Schleich et al. [116] introduced a product DT based on the concept of "Skin Model Shapes" to bridge the design and manufacturing stage. Tao et al. [128] conceptualized DT applications for design, manufacturing, and service stages to solve challenges with life cycle data such as information islands and duplicates of data. Agnusdei et al. [3], Atalay et al. [11], Ciano et al. [30], Liu et al. [76] presented state-of-the-art, evolution, enabling technologies, and industrial applications of the DT concept for all life cycle stages. The synergy of DT and PLM has the potential to fully integrate products and production processes. The synergy between these two concepts can facilitate the creation of a comprehensive digital thread that provides real-time feedback on the performance of the product throughout its life cycle. This can enable predictive maintenance, reduce downtime, and improve the overall efficiency of the production process and the performance of the product. An essential obstacle to overcome in order to fully realize the potential of DTs in PLM pertains to the utilization of data collected by the Internet of Things.

A third research area describes DTs as enablers for SM and Smart Factories. Tao and Zhang [132] conceptualized shop floor DTs and studied operation and implementation methods for SM. Qi and Tao [106], Zhuang et al. [154] described the synergy of Big Data and DT as an enabler for SM, where data analytics lead to intelligent behavior of systems, and DTs integrate virtual and physical entities. Like DTs the interest in SM is rapidly increasing, while a key challenge is the maturity level of Industry 4.0 readiness which may result in the majority of the implementation of DTs for SM being related to data acquisition and visualization. Seldom DTs leverage the potential for real-time interaction. To exploit the potential benefits, potential research directions include (i) achieving real-time connectivity and interaction, (ii) developing high fidelity models, (iii) balancing cost-benefit tradeoffs of DTs, and (iv) identifying advanced (novel) applications for DTs.

Other research focuses on the state-of-the-art, evolution, and applications of DTs. Jones et al. [61] identified 19 themes related to DTs and list historical developments related to DTs, i.e., computer-integrated manufacturing, virtual manufacturing systems, model-based predictive control, machine monitoring, advanced control, and build information modeling. Additionally, Sjarov et al. [121] compared DT architectures to achieve a more unified DT reference architecture. Tao et al. [131] described the development and application of DTs in an industrial setting. Melesse et al. [88] reviewed the value of DT applications for production, predictive maintenance, and after-sales services. Finally, Lu et al. [81] found that the majority of DT applications were either monitoring (status monitoring and process visualization) or prediction (fault prognosis, PLM, and process optimization). In summary, the state-of-the-art, evolution, and applications of DT are being extensively researched. Researchers are working towards improving DT architectures, developing new applications, and exploring the value of DT for various industries. The findings of these studies can inform the development and implementation of DT systems that enable more efficient, effective, and reliable manufacturing processes.

With a more mature understanding of DTs, recent reviews focus on specific application domains such as maintenance [34], intelligent welding systems [137], additive manufacturing [146], sustainability [47] and turbomachinery [142]. All these studies target specific manufacturing processes and focus on individual use cases. This may indicate that a fundamental understanding of DT technology has led to a more application-specific focus. However, as evidenced by the literature, challenges remain regarding the limited interoperability of these DT applications for coupling several DTs, integration of DTs with the control system for sending feedback, and lack of full DT solutions providing all relevant services in a single application.

The study considered most related to our research work is Cimino et al. [31], which reviewed DT applications with a focus on practical implementations from 2015 to 2019. Similarities to our study can be found in terms of (i) focus on implementations and excluding articles without practical implementations, (ii) description of how data acquisition and simulation were implemented, and (iii) scope of the manufacturing domain. However, this study has significant differences compared to our study: (i) our study provides more details and challenges related to unit level DTs, (ii) we described generic reference models for the development of manufacturing DTs, and (iii) we included a more comprehensive selection of articles with a more defined focus (their systematic search included 52 articles while we considered 96).

To summarize, none of the papers provides a comprehensive and detailed overview of generic reference models, modeling and data, hardware and software, and services of DTs at the unit level as seen from Table 1. We end this comparison by stating the main challenges

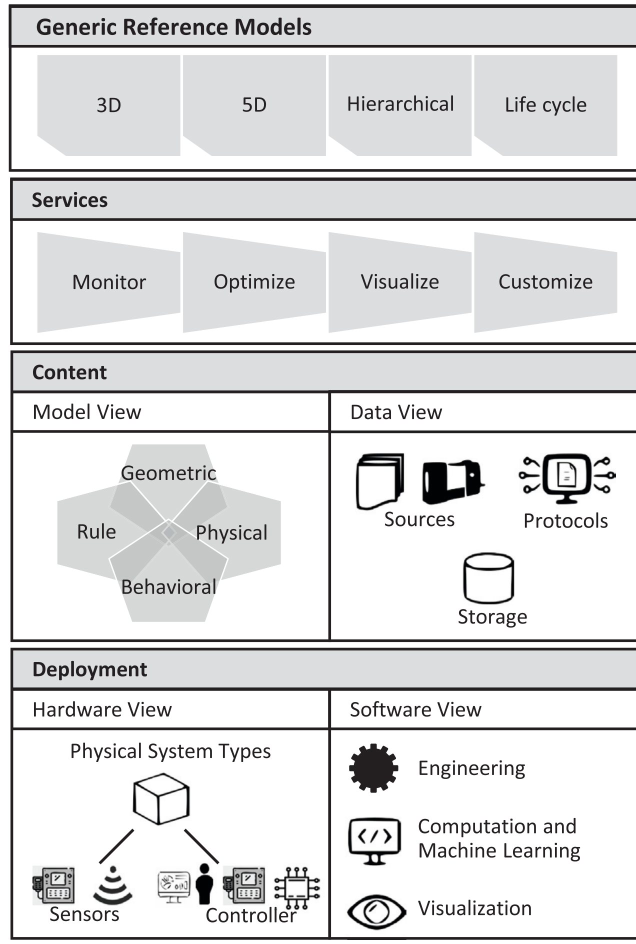


Fig. 2. Overview of the four categories surveyed in the following sections of this paper.

that are a common theme in DT research today. First, papers focus on developing specific digital twin components. Second, the DT implementations fundamentally differ from each other. Third, various frameworks and reference models of DTs exist, but they have yet to become industry consensus. The above challenges collectively hamper the efforts to conduct systematic research [76].

Research methodology

This literature review follows a systematic deductive review process [122]. The deductive approach is particularly suitable to cope with an abundance and ever-rising number of sources in a topic such as DTs. The systematic deductive review follows a stringent process for collecting articles, followed by an analysis of them using pre-defined categories. We define four categories, as shown in Fig. 2: generic reference models, services, content (models and data), and deployment (software and hardware).

The aim of this review is threefold: 1) to provide an overview of manufacturing DTs at the unit level, 2) to guide engineers towards practical DT applications, and 3) to support the manufacturing industry by summarizing key technologies, and outlining challenges and limitation of state-of-the-art DTs. This review focuses on unit level applications of DT, based on SCOPUS-referenced research publications and does not include applications from alternate venues, such as industrial reports. Discussion regarding industrial practices on unit level DTs is beyond the scope of this review, and interested readers are referred to industry-focused publications in this area [2,99,100]. The research question we address in this contribution is:

“What methods and technologies are used for engineering and deploying manufacturing DTs at the unit level?”

This research question is broken down into four questions related to the pre-defined categories: .

1. What generic reference models exist and are being used for conceptualizing unit level DTs? This research question seeks to identify generic reference models reported by academic research to obtain a collection of original reference models and to explore whether there is a broad consensus on using certain reference models within specific application domains. (answered in the section Generic Reference Models for Digital Twins)
2. What services are provided by these DT implementations? This research question seeks to identify services that can be offered by implementing manufacturing DTs at the unit level and provide insights into the potential benefits and applications of DT technology. (answered in the section Digital Twin Services)
3. What models and data (content) are required for engineering these DTs? This research question aims to investigate the essential models and data contents required to engineer DTs, which can give valuable knowledge about them to investigate the essential models and data content required to engineer DTs, which can give valuable knowledge about the technical requirements for developing and implementing DT technology. (answered in the section Digital Twin Content)
4. What software tools and hardware systems are used for deploying these DTs? This research question investigates the software tools and hardware systems that are utilized for the deployment of DTs, providing insights into the technical infrastructure required for the successful application of DTs. (answered in the section Digital Twin Deployment)

To comply with the systematic deductive process, we follow a four-step approach: .

1. Searching for relevant articles based on their title, abstract, and keywords in the Scopus online database using specific query strings and limiting to relevant subject areas resulted in 1409 original retrieved documents.
2. Filtering the results by screening titles and abstracts using inclusion criteria reported below resulted in 335 papers.
3. Conducting a full-text assessment of remaining papers resulted in 96 studies included for detailed evaluation.
4. Evaluating the 96 papers for the pre-defined categories: generic reference models, services, model and data content, and hardware and software deployment.

Table 2
Retrieval catalog of the literature review.

Retrieval catalog	Detail content
Database	Scopus
Query strings	TITLE-ABS-KEY(“Digital Twin” AND (“Production” OR “Manufacturing”))
Subject areas	Engineering, Computer Science, Material Science
Time frame	up until 04.2021
Document results	1409
Papers filtered	96

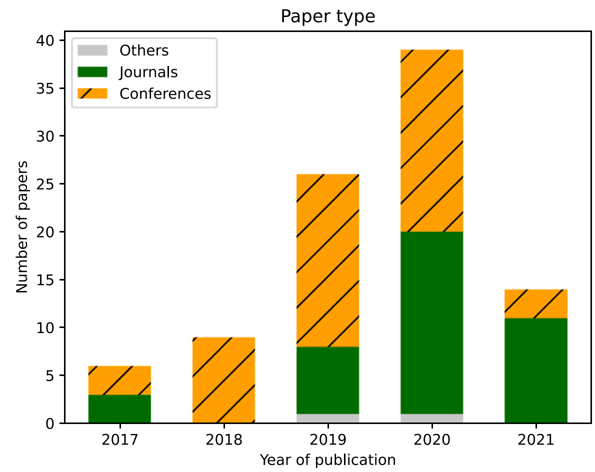


Fig. 3. Types of papers published per year.

Following, we list the inclusion criteria for filtering the papers: .

- Papers in English and which are accessible online;
- Papers confined to a contribution to DT research;
- Papers describing either engineering of partial DTs, i.e., DT components such as models or data pipelines, or implementations of entire DTs;
- Papers on single manufacturing entities such as machine tools and advanced robotic applications, i.e., that do not focus on system and system of systems level;

Table 2 shows the retrieval catalog of this literature review: the database, query string, subject areas, time frame, the original number of papers, and the number of papers included for review.

We present quantitative results on the filtered set of papers that describe practical implementations of manufacturing DTs at the unit level in the section Quantitative analysis. Followed by a qualitative analysis of the four pre-defined categories in the section Review of Unit Level Manufacturing Digital Twins.

Quantitative analysis

Before diving into the qualitative review, we quantify noticeable metrics of the filtered papers. In particular, the quantitative analysis contains a summary of the types of papers by year, an overview of journals and the number of associated papers, a summary of publications by country, and a word cloud of all keywords of the filtered papers.

Of the selected papers, 54 % are conference proceedings, 41 % are published in journals, and 4 % are book chapters and technical reports. Fig. 3 shows that the research interest in unit level DTs has

Table 3
Distribution of papers by journals. We summarized journals to which a single paper was associated as *Others*.

Journal title	# Papers
International Journal of Advanced Manufacturing Technology	5
International Journal of Computer Integrated Manufacturing	5
International Journal of Production Research	3
Journal of Intelligent Manufacturing	3
Journal of Ambient Intelligence and Humanized Computing	2
Robotics and Computer-Integrated Manufacturing	2
IEEE Access	2
Others	18
Total	40

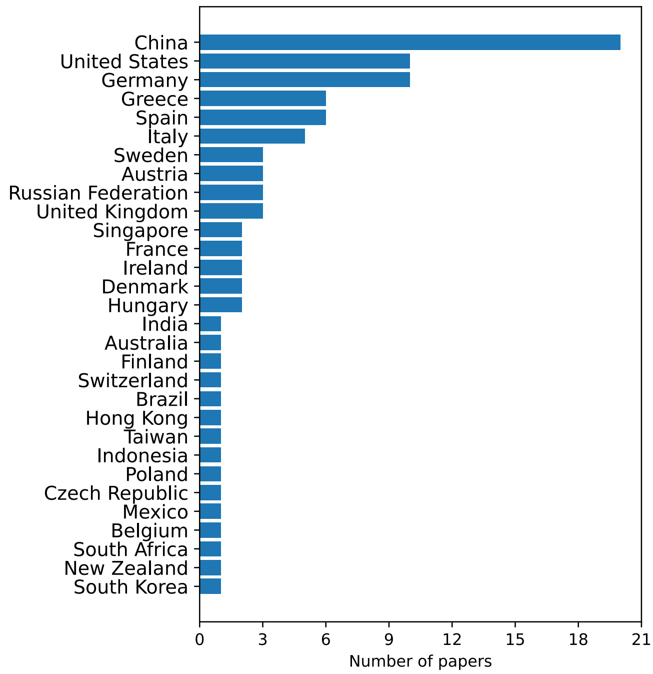


Fig. 4. Number of papers published per country.

risen over the last few years. Prior to 2017, no papers had been obtained. One reason may be that relevant technological advances related to Industry 4.0, such as digitization of manufacturing machines, adoption of the Internet of Things, and development of computational intelligence, must be matured before implementing DTs at the unit level. The number of journal papers increased in 2019, and in 2020, an equivalent number of papers were published in journals and conference proceedings. Note that only the first quarter of 2021 was included in this review; thus, we expect this trend to continue.

Table 3 displays the number of selected papers per journal. The two journals with five associated papers are the International Journal of Advanced Manufacturing Technology and the International Journal of Computer Integrated Manufacturing. The rest of the papers belong to other journals.

Fig. 4 shows that most papers related to DTs at the unit level come from China (20), followed by the United States and Germany (10), Greece and Spain (6), and Italy (5).

Fig. 5 shows a word cloud built from the papers' keywords. The font size in the word cloud is proportional to the frequency of the word inside the keywords. Words that occur with a high frequency are DT (67), manufacturing (38), system (29), simulation (16), and cyber-physical (14).

Review of unit level manufacturing digital twins

We followed a top-down approach, listing prominent DT generic reference models in the section Generic Reference Models for Digital Twins. Next, section Digital Twin Services focuses on the services provided by DTs. Then, section Digital Twin Content details model and data resources for enabling the services, and section Digital Twin Deployment shows how to bring those resources into action using software and hardware.

Generic reference models for digital twins

Most papers (75 out of 96) included a generic DT model. We identified four generic model types: the three- and five-dimensional models, hierarchical models, and life cycle models. A minority of papers reported generic models that did not complement the four categories. We did not include information on the latter generic models.

A generic model acts as a skeleton at the macro level that contains design patterns for organizing DT applications while giving developers the freedom to fill in content (data and models) and to select an implementation strategy (hardware and software). These architectural styles are common in software architecture research [39]. Below, we listed and classified generic reference models of manufacturing DTs at the unit level.

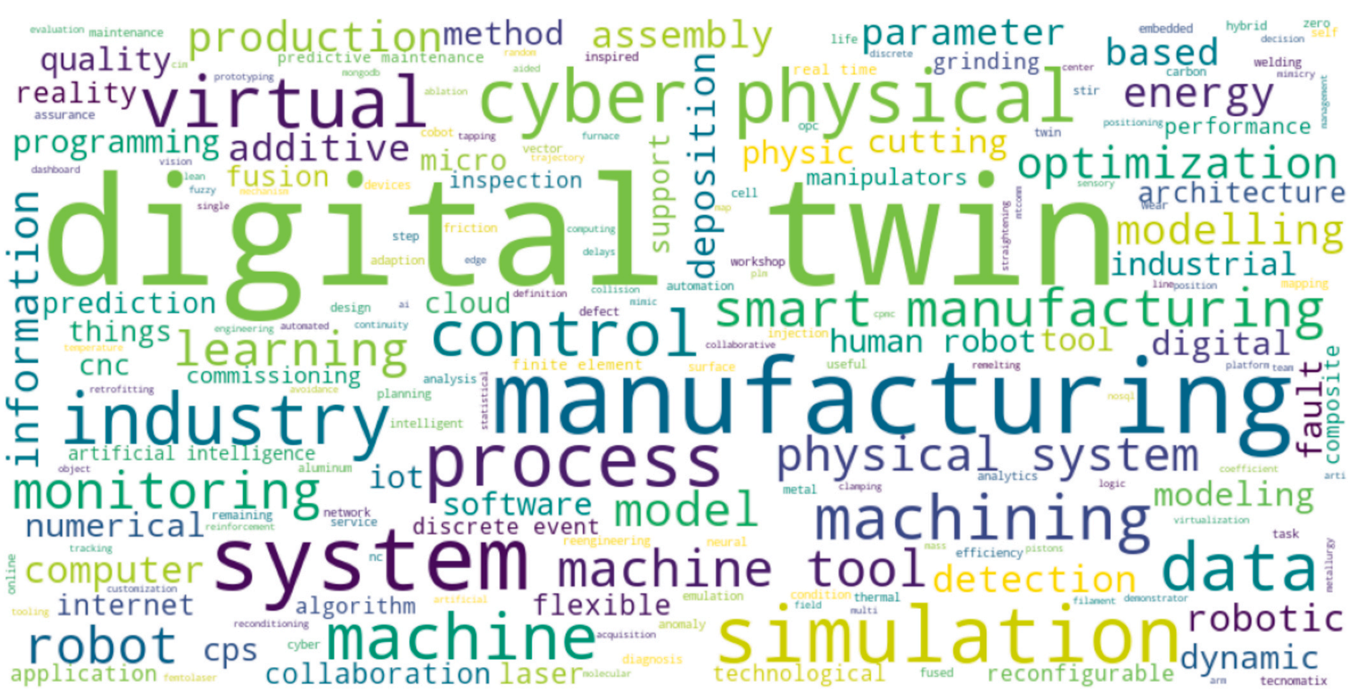
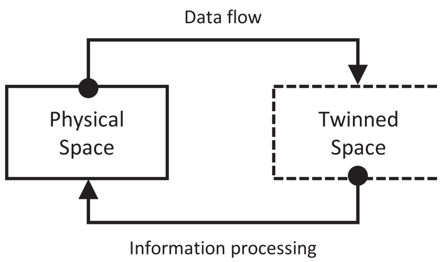
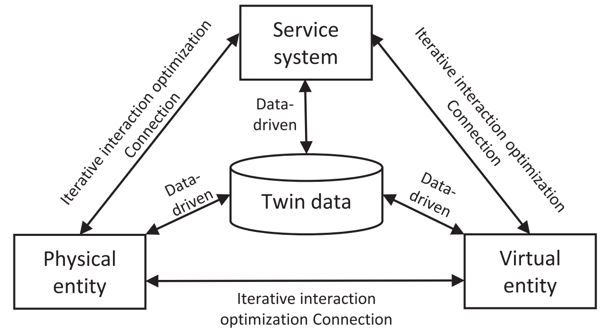


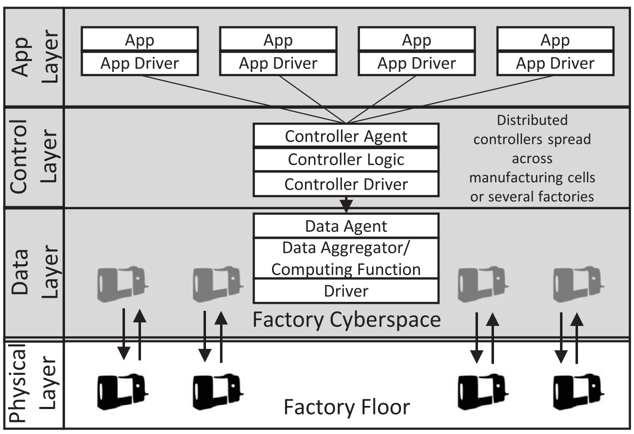
Fig. 5. Word cloud of scientific keywords from the papers.



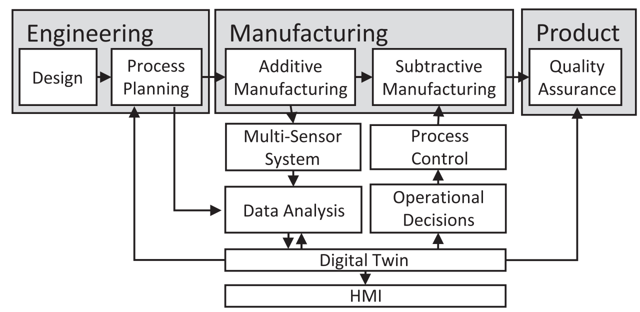
(a) Three-Dimensional reference model. Adapted from [77]



(b) Five-Dimensional reference model. Adapted from [139]



(c) Hierarchical reference model. Adapted from [9]



(d) Life cycle reference model. Adapted from [112]

Fig. 6. Four examples of generic reference models of a DT system. The reference models represent the structure of the subsystems of the DT systems and describe behavior between those subsystems.
(a) Adapted from [77]; (b) Adapted from [139]; (c) Adapted from [9]; (d) Adapted from [112].

Three-dimensional and five-dimensional reference models

We found that the three-dimensional (3D) reference model was the most widely used architecture for constructing DTs at the unit level (29 out of the 96 papers mentioning this). Grieves [42] introduced the 3D reference model consisting of a physical space, a virtual space, and a data flow and information processing between them. Fig. 6a exemplifies the 3D reference model.

The terms *physical space, physical system, physical object, physical machine, physical twin, physical model, real product, or real machine* were used to describe the physical entity. The papers associated various kinds of physical objects with the physical space of a DT (machines, auxiliary equipment, tools and work-pieces, processes, perception systems, communication networks, actuators, and control systems).

The terms *virtual space, digital space, cyber space, cyber system, twinned object, virtual machine, product model, and hardware in the loop* were used to describe the virtual entity. The papers associated various kinds of models (3D, kinematic, physical, finite element analysis, simulation, decision-making, information, ontology, control, and communication emulator), data storage technologies, signal processing techniques, and service applications (visualization, interaction, self-update, model calibration, adaptive control) with the virtual space of a DT.

The terms *bi-directional connection, information processing, data mapping, data server, application mapping, digital thread, interaction* were used to describe the connection and information exchange between the physical and virtual space. The papers characterized the physical-to-virtual flow with the terms *real-time perceptual data, real-time data sensing, sensor data, data gathering, data flow, measurement results, manufacturing data, sensor data, trace*. In turn, the virtual-to-physical flow was characterized by the terms *optimization instruction, intelligent using strategy, simulation data, decision and control, feedback control, information exchange, diagnosis, prognosis, and optimization*.

The 3D reference model focuses on the conceptual aspects of the DT, setting the main terms. Thus, DT researchers often use it to introduce DTs and DT working principles to a scientific audience. Additionally, the 3D reference model offers a significant degree of freedom to the DT engineer. This freedom allows for different interpretations leading to fundamentally different implementations of DTs (which also lead to the notion of a claimed DT, i.e., Digital Model and Digital Shadow versus actual bi-directional DT, see [66]).

As a result, the need for the five-dimensional (5D) reference model appeared to engineer DTs for an industrial setting. The 5D reference model extends the 3D reference model by data and service dimensions. With the data and service dimensions, the 5D model provides a central storage location connected to the physical, virtual, and service space and a service system for implementing data-driven services [133]. The 5D reference model enables developing higher-value adding and personalized services while the 3D reference model can only “achieve simple physical-virtual interaction [137]”. Fig. 6b exemplifies the 5D generic reference model.

Hierarchical reference models

Hierarchical reference models focus on organizing the DT elements’ subsystems in layers. Fig. 6c exemplifies a four-layer hierarchical reference model. Depending on the specific hierarchical model implemented in the papers, the number of layers differed between three to six. For example, Park et al. [98] described a three-layer model (factory layer, twin layer, and application layer), where each layer has several subsystems that link to functionalities in higher-level layers. Further, Angrish et al. [9] introduced a four-layer model for managing virtual machines conceptually similar to Manufacturing Execution System and Enterprise Resource Planning system for the physical shop floor. In Angrish et al's. [9] reference model, each physical machine requires a specific machine driver and database, i.e., to connect to N machines N machine-specific implementations of the reference model are required, with the exception of the top application layer that may access and analyze data from multiple machines. Shahriar et al. [118] presented another four-layer model (resource layer, visualization layer, cloud layer, and application layer) for a cyber-physical manufacturing cloud. This generic model aims to run on multiple computing platforms through a client-server model for operating machines through DTs and to visualize operations at a granular level in 3D. Last, Redelinghuys et al. [111] outlined a six-layer model (physical device layer, physical data collection and local control layer, local data repositories layer, data to information conversion layer, cloud-based information repository layer, and emulation and simulation layer). The authors claimed that the reference model is independent of application-specific details, suited for creating DTs of legacy systems, allows high-fidelity visualization and integrates elements developed by different parties.

Some hierarchical models relied on industrial standards and reference architectures such as ANSI/ISA-95 [136], RAMI4.0 [6], VDI 3682 [20], ARTI (holonic manufacturing systems) [24], and MIMOSA OSA-CBM standard [25].

Life cycle models

Life cycle reference models connect information from different phases of the product and manufacturing life cycle using DTs. Fig. 6d exemplifies a generic life cycle DT model. For example, Chhetri et al. [28], Cao et al. [23] presented a reference model linking the DTs of a product and a manufacturing process. Main emphasis was placed on the conversion of design information Computer Aided Design (CAD)/ Computer Aided Manufacturing (CAM) into STEP-Numerical Control (NC) code, linking monitoring data and design data, and simulating part geometry online. Furthermore, Reisch et al. [112], Söderberg et al. [123] described a generic DT model covering the design, manufacturing, assembly, and inspection phase. Also, Pombo et al. [104] described a generic DT model with the potential of knowledge sharing between distributed agents in the manufacturing life cycle. Information exchanges between products and production can facilitate traceability of products throughout the production and use phase and can enable the manufacturer to determine root causes related to product defects and inefficiencies. In particular, the interplay of technologies such as centralized repositories for data storage, connectivity of relevant physical assets, and mechanisms for autonomously adapting the physical assets to disturbances have the potential to increase production efficiency and reduce waste. Despite this potential, most life cycle models presented in the literature are use-case specific and cannot be applied generically to other use cases. Thus, a key requirement for providing comprehensive overviews of entire manufacturing operations and for decreasing the effort of developing lifecycle DT models by making those models reusable, is the creation of methods to integrate life cycle reference models from different use cases.

Summary and discussion of digital twin generic reference models

To summarize, we found four types of generic reference models that were adopted for a wide range of DT applications (3D, 5D, hierarchical, and life cycle reference model). Of these, the 3D and 5D reference model were the most widely used. This widespread usage may result from the fact that the 3D and 5D reference model are highly conceptual; the more application-specific a generic reference model is, the less applicable it becomes to a generic use case. Due to the large design freedom of the 3D and 5D reference model, it is easy to formulate an application that can fit with them. The drawback of the 3D and 5D model is that they do not provide a summary of methods that can be used for engineering the individual DT elements. Further, the 3D and 5D model are only applicable during DT design without specifying DT operation. Our review suggests no agreement exists on when to use which generic reference model and how to apply it. However, DT practitioners typically rely on different application-specific models [130]. Overall speaking, DT practitioners still need guidance on selecting and configuring an appropriate reference model for a specific application.

Standardization of generic reference models needs to be agreed upon. To date, not even a standard naming convention for a generic reference model exists, as evidenced by the fact that DT practitioners refer to "generic models" using several terms, e.g., *architectures, frameworks, concepts*. Also, components within a DT do not have standard terminology. Lack of standard terminology can challenge communication with partners, suppliers, and customers, hinder defining DT building blocks, and complicate the specification of project requirements and access to funding for engineering DTs. By now, multiple DT standards are being developed or were only finalized most recently by institutions such as the International Standards Organization [58], the Industrial Digital Twins Association with the Asset Administration Shell, and the Digital Twins Consortium with a collection of open-source software. An overview of SM related standards for the development of DTs is provided in [81]. Having multiple standards continues the problems of vague terminology, making it a precondition that standardization committees attempt to converge on a single DT terminology. With a defined terminology and standards in place, we believe that a more unified description of DT will be adopted, which can help to reduce the obstacles when engineering DTs in manufacturing drastically.

Moreover, unifying the process for constructing a generic model can help to specify responsibilities in the interdisciplinary effort to engineer DTs, and to simplify maintaining DTs deployed in the field. Note, that we recommend unifying the process, not the model itself, as diverse application cases drive most models. Additionally, this points to a broader knowledge gap in that generic reference models require specifying the responsibilities of individuals in the effort to engineer DTs. Thus, allowing for standard operating procedures, i.e., step-by-step instructions when engineering DTs. Likewise, with a unified process, elements of a reference model can be matched to people skills and insights into the specific equipment and processes. For example, CAE engineers can build models, data engineers can develop monitoring and data processing systems, and software engineers can develop relevant applications and maintenance plans.

Interoperability becomes essential to enable a system-of-systems approach for DTs, i.e., to enable unit level DTs to work with one another horizontally and to exchange information vertically across hierarchies. As we pointed out in Fig. 1, a manufacturing enterprise consists of manufacturing facilities. Each of these facilities is, in turn, composed of unit-level entities such as machine tools, advanced robotics, and additive machines. Besides the interplay of DTs, components in a single DT (services, data, models, hardware, and software) face significant challenges in achieving seamless integration. Distribution of some of these components can further increase the challenge of interoperability. Therefore, there exists a need to rely on existing standards to construct composable, reusable, and scalable DTs. At the unit level, only a few hierarchical generic models are based on industrial standards, such as ANSI/ISA-95 [136], RAMI4.0 [6] and VDI 3682 [20].

Digital twin services

Following, we categorized the services by four types and report the findings in the sections Product Customization, Visualization,

Table 4
Overview of services provided by the unit level DTs grouped by four categories: Product customization, visualization, monitoring, and optimization.

Category	Subcategory	Idea	Reference
Product customization	Geometric variations management	Adopt the assembly strategy to compensate for geometric variations	[102,123]
	Assembly planning	Plan assembly sequence autonomously based on product description provided by user	[51]
	Adaptive modeling	DT-based adaptive modeling for machining process	[77]
Visualization	3D interactive visualization	Real-time display of manufacturing equipment, process and product by 3D simulation	[56,59,91,105,114,118,148,149]
	Graphical visualization	Visualizing machine status through real-time data mapping e.g., in a dashboard	[20,21,23,50,134,138,153,152]
Monitoring	Condition and health monitoring	Monitoring parameter for identifying status, faults and remaining useful lifetime of equipment	[5,15,18,25,35,80,84,83,89,98,103,108,111,114,119,140]
	Quality monitoring	DT-driven evaluation of product quality	[22,141,92,151,55,44,115,28,112,14,144,37]
	Model calibration	Determine system parameter describing real system behavior offline	[143,10,68,110,136,5]
	State estimation	Updating model state and parameters by fusing model output and data online	[5,10,12,26,28,83,96,105,108,111,127,145,147,149]
Optimization	Machine and process setup	Reduction of effort to setup a production machine and process through DT	[19,110,74]
	Parameter optimization	Determining optimal process parameters with respect to business objective using DT	[101,13,27,134,33,151]
	Sustainability	Reduce sustainable indicators such as carbon emission, energy consumption	[150,143,136,24,72]
	Virtual commissioning	Virtual Training and What-if simulation to determine optimal setup with respect to productivity, ergonomics	[72,54,46,86,85,36,12,93,70,96]
	Path planning	DT-driven optimization of robot movement for assembly and avoidance of obstacles	[16,62,127,124]
	Process planning	Determine optimal process plan using DT	[75,82]
	Motion control	Controlling manufacturing equipment through DT	[87,6,52]
	Adaptive control	Control manufacturing process to yield optimal product quality based on DT	[126,145,117,139]

Monitoring, and Optimization. Table 4 offers an overview of the different services and associated references.

Product customization

Complying with quality requirements while allowing customization of products requires methods to adjust manufacturing and assembly strategies. To date, human workers, such as process planners or operators, frequently need to adapt the process settings to satisfy quality requirements. However, DTs can automate adjusting required settings. Three different methods were reported in the reviewed papers: Geometric variations management, assembly planning and adaptive modeling.

Geometric variation management can compensate for deviations of individual parts due to inherent process variability and physical phenomena such as wear, thermal expansion, and part deformation. DTs can help to develop robust products and optimize the process to minimize the effect of geometrical variations. Geometric variations management requires a flow of information from part design and manufacturing to assembly. For example, Söderberg et al. [123], Polini and Corrado [102] described self-compensating assembly for minimizing geometric deviations using part and process DTs.

Assembly planning methods require compensating for product variations and customization to ensure product quality, life, and maintainability. However, a large number of variants increases the cost and complexity of assembly planning. DTs can use part information from design and manufacturing to automatically plan the assembly process. For example, Hoebert et al. [51] reported a DT service for planning the optimal assembly sequence by providing a final product description.

Adaptive modeling can help to update product and process models by variations introduced during manufacturing. The virtual entity model of the physical system is created using adaptive modeling by observing the product status in real-time, analyzing product modifications, and making control decisions via bi-directional interaction. For example, Liu et al. [77] fused the product's physical properties, including material attributes and structure performance, with process planning data and real-time machining information to obtain an as-manufactured part representation.

Visualization

DT information can be visualized using graphical tools such as dashboards and through a dynamic 3D representation of the physical entity.

Graphical visualization can allow users to monitor and gain oversight of specific attributes such as status, condition, and operation of processes, machines, or products. Graphical visualization presents the raw sensor data and derived results with different means, such as bar charts, time series signals and various attributions via dashboards. Furthermore, this visualization tool can help machine operators and experts better understand and control the system. For example, Wang et al. [138] developed a dashboard showing machine health status, production efficiency, and order scheduling. Also, Tong et al. [134] presented HMIs and applications for visualizing and analyzing machining trajectory, machining status, and energy consumption.

3D interactive visualization in manufacturing has many advantages. One of the benefits is that it provides a more intuitive and immersive experience for operators, technicians, and process planners to better understand the manufacturing process, equipment, and product. Using real-time visualization of manufacturing equipment, operators can quickly detect issues and identify the root cause of problems. They can also test different scenarios and configurations in a virtual environment before implementing changes in the actual process. Another advantage of 3D interactive visualization is the ability to create virtual models of manufacturing equipment based on physics-based and kinematic models. For example, Tong et al. [105] developed a virtual model of a grinding machine based on 3D, physics-based, and kinematic models that can accurately reflect the equipment's real-time status and process, allowing operators and technicians to optimize their maintenance and repair activities. Additionally, 3D interactive visualization enables remote access to the physical system Shahriar et al. [118]. This feature allows experts to provide remote support and troubleshoot problems without having to be physically present at the manufacturing site. Cloud-based access to manufacturing resources also enables collaboration between different teams and experts from different locations, improving the overall efficiency of the manufacturing process. Finally, manufacturers can obtain more comprehensive data and analysis of their manufacturing processes by combining 3D interactive visualization with other methods, such as dashboard monitoring. For example, Zhao et al. [149] combined dashboard and 3D interactive visualization for a Programmable Logic Controller (PLC) of a milling machine. They based their method on STEP-NC to facilitate CAD/CAM exchange to CNC, a unified data access method, and a simulation environment. The method enabled simulating workpiece shape and calculating process indicators such as cost and machining time per tool. This information can be used to optimize the process, reduce waste and costs, and improve the overall quality of the product. Overall, using 3D interactive visualization in manufacturing has numerous benefits that can significantly improve the efficiency and effectiveness of the manufacturing process.

Monitoring

Monitoring is an essential aspect of modern manufacturing processes. It involves observing machinery for faulty behavior and tracking product quality across manufacturing operations. The main goal of monitoring is to detect any potential problems in the process as early as possible and take corrective action before they become significant issues. By monitoring equipment and product quality, manufacturers can ensure that the process is running smoothly, reduce downtime, and improve the quality of the final product. Moreover, monitoring can help manufacturers meet regulatory requirements and industry standards. By monitoring the manufacturing process and tracking product quality, manufacturers can ensure that their products meet these standards and comply with regulations. This can help to protect their reputation and avoid costly penalties for non-compliance. Therefore, by using monitoring as part of their overall manufacturing strategy, manufacturers can improve their bottom line and deliver high-quality products to their customers. Different categories of monitoring in reviewed papers are explained in the following.

Condition monitoring is a critical aspect of modern manufacturing processes, allowing manufacturers to detect faults and issues with their equipment. By continuously monitoring the health status of machines, equipment, and tools, manufacturers can identify potential faults and optimize their maintenance schedules to reduce downtime and avoid expensive emergency repairs. Moreover, DTs can help manufacturers reduce their maintenance costs by providing insights into the root causes of faults and issues to prevent them from occurring in the future. This can help manufacturers extend the equipment's lifespan and reduce the need for costly repairs and replacements. With the help of DTs, manufacturers can detect these issues in real-time and take corrective action before they become significant problems. For example, Redelinghuys et al. [111] proposed a DT architecture and implemented it for a pneumatic robotic gripper for detecting anomalies - pneumatic cylinder leakages and bearing failures. Miao et al. [89] demonstrated a DT framework using multidimensional time series data for anomaly prediction and equipment state monitoring for CNC machines. Moreover, predictive maintenance is necessary for machine tools to avoid faults, waste, and machine downtime. For example, Luo et al. [83] developed a predictive maintenance approach overcoming status variety and inconsistencies of CNC machine tools during their usable lifetime.

Quality monitoring using DT-driven processes can help to avoid defects and ensure consistent products with the expected level of quality. While traditional quality monitoring methods are time-consuming, labor-intensive, and often fail to identify defects, DTs technology offers a more efficient and effective approach to quality monitoring. Analyzing data from the virtual model allows manufacturers to identify patterns and trends that may indicate potential issues and take corrective action before defects occur. Therefore, this can reduce the number of defects in the production process, improve product quality, and ultimately increase customer satisfaction. Moreover, DTs enable companies to conduct virtual testing and simulations, reducing the need for physical prototypes and minimizing the time and cost associated with traditional testing methods. By identifying and addressing quality issues earlier in the production process, companies can avoid costly rework and reduce the risk of product recalls, protecting their reputation and bottom line. For example, Cai et al. [22] developed a DT-based predictive model for surface roughness quality in machine tools based on manufacturing and sensor data. Similarly, virtual quality has been considered by Xi et al. [141] to achieve high quality in the workpiece surface finishing. In addition, Moretti et al. [92] addressed the challenges of optical quality control for additive manufactured parts by developing multiple DTs to plan the inspection process, supporting edge detection by guiding the microscope to areas of interest, and producing a geometric comparison of the part. Furthermore, Hürkamp et al. [55] combined simulation and machine learning for analyzing the quality of overmolded parts, and for predicting the quality of the overmolded parts on-line based on process settings.

Model calibration is a crucial step in developing models that accurately represent the behavior of physical systems. While model parameters can often be estimated from theoretical calculations, these estimates are often not accurate enough to capture the complexity of real-world systems. As a result, calibration is necessary to adjust model parameters so that the model accurately represents the physical system response. Design of Experiment (DoE) and optimization methods are commonly used for model calibration. For example, Yan et al. [143] demonstrated using a designed trajectory test for exciting a robotic manipulator and identifying the coefficient matrix of the linear model and dynamic parameters through a least squares optimization procedure. Similarly, Arkouli et al. [10] used designed trajectories combined with a recurrent neural network to calibrate their model. Full inverse analysis is another optimization method used to determine model parameters [68,110]. In some cases, parametric and static variables can be obtained directly from data sheets or CAD models. For example. Similarly, Aivaliotis et al. [5] extracted robot parameters such as joint type, distance, angle, link twist, and length from data sheets and used those parameters to initialize the model. [136]model variables such as mass, center of gravity, inertia tensor, and axis of links from a CAD model. Overall, model calibration is a critical step in the model development process, and it requires careful consideration of the available data and appropriate calibration methods to ensure that the model accurately represents the physical system response.

State estimation updates model parameters online to obtain the best fit between monitoring data from the physical system and the model response during DT execution. State estimation of variables during DT operation can be achieved through model and data fusion algorithms, direct mapping methods, and data-driven algorithms. Furthermore, weight tables combined with update rules can help to limit computationally expensive update procedures to situations where updates are necessary.

Fusion of model outputs and measurement data through adequate algorithms can be used for iteratively updating a model and achieving higher model accuracy. For example, Chen et al. [26] fused sensor data and computational model outputs to iteratively update model parameters before solving the governing equation. Similarly, Luo et al. [83] updated the state space model with measured values after every process step and then fused the state space outputs with results from a data-driven model using a particle filter algorithm.

Other authors mapped measurement data from the physical entity to the inputs of the virtual entity model. Direct mapping methods are most suitable for updating a geometric model of the physical entity. For example, Redelinghuys et al. [111] implemented a method called every time a data value changes on the OPC-UA server to update the geometric model in soft real-time. Similarly, Zhao et al. [149] mapped the real-world tool position to drive the material removal model. In addition, Tammaro et al. [127] specified the 3D content of a robot system and surrounding objects in Extensible Markup Language (XML) and updated the specifications to reflect changes in the physical entity, and Qi and Park [105] directly mapped Programmable Logic Controller (PLC) control signals to the corresponding sensor and actuator signals of the virtual entity. For validating the accuracy of the PLC input/output mapping, Ayani et al. [12] manually forced actuator movements on the physical entity and monitored input signals to the virtual entity, and Orive et al. [96] compared control system responses and outputs of the virtual entity model for designed scenarios.

Another method for online updating relies on data-driven approaches and rules defining a threshold for updating model variables. For example, Chhetri et al. [28] initialized fingerprints of optimal product using a Birch clustering algorithm on individual channels, monitored variation by comparing the average silhouetted score, and updated initial fingerprint libraries based on a majority vote for all channels. Similarly, Qiao et al. [108], Zhang et al. [147] used a rule model defining a threshold to update model parameters through backpropagation and decoder networks.

The update frequency of parametric values can limit models' simulation speed and performance. To reduce the frequency of updates and thus free computational resources and speed simulation execution, a weight factor table, reflecting the importance of model parameters on model accuracy, can be used. For example, Arkouli et al. [10] used weight tables for assigning an importance score to each variable which determined the respective update frequency.

Similarly, Aivaliotis et al. [5] monitored selected parameters and updated those using nonlinear least squares; Zehetner et al. [145] identified constant machine parameters at every startup and only calibrated slowly changing parameters during standard service procedures of the machine; and Zehetner et al. [145] updated material and workpiece parameters which have high variance and are sometimes not known in advance once per part.

Optimization

Optimization aims to improve performance and efficiency while meeting specific goals in manufacturing operations. DT technology can significantly enhance optimization by providing accurate and real-time data and models. By leveraging data and models, DT can identify areas for improvement and optimize manufacturing processes to improve performance, reduce waste, and increase sustainability. Several focus areas of DT-driven optimization have been identified, including virtual commissioning, parameter optimization, and sustainability improvements.

Virtual commissioning is a valuable tool that can significantly improve the efficiency and safety of manufacturing operations. By creating a virtual representation of the manufacturing system, manufacturers can identify potential issues and optimize the layout and design of workstations before making physical changes. One significant advantage of virtual commissioning is mitigating operator risks and evaluating safety issues before changing the physical system. Moreover, virtual commissioning can help identify optimal workstation layouts and improve efficiency. This can significantly improve productivity and reduce the risk of operator fatigue and injury. One example of virtual commissioning is demonstrated in a study by Ayani et al. [12]. The authors used an emulation tool for retrofitting and reconditioning a legacy machine tool. By using the virtual entity of the DT to identify and resolve problems before physical implementation, the authors could reduce commissioning time and ensure that the physical system was optimized for efficiency and safety. Overall, virtual commissioning is a powerful tool that can greatly enhance manufacturing operations.

Parameter optimization through DTs can enhance process performance by selecting the optimized process parameters. DTs can simulate different scenarios and test various parameters to find the optimal process settings. This can lead to significant improvements in quality, efficiency, and cost-effectiveness. For example, Tong et al. [134] developed a DT of a cutting machine tool to optimize machining dynamics and to estimate and compensate for contour errors. Furthermore, Balderas et al. [13] applied ant colony optimization for manufacturing hole patterns on printed circuit boards using minimal trajectory and tool change time. Moreover, Pereverzev et al. [101] used dynamic programming to optimize a grinding process regarding processing time, feeds, and product quality requirements.

Sustainability related DTs services can enhance decision-making and operations related to sustainability goals. DTs can simulate different scenarios and test various parameters to find the most sustainable and environmentally friendly options. One key application is the optimization of CO2 emissions in manufacturing processes, which can help reduce the carbon footprint and meet sustainability targets. For instance, Zhao et al. [150] developed a DT solution to optimize the carbon emissions of CNCs milling machines. The researchers used a combination of simulation and optimization techniques to identify the optimal machining parameters that would minimize the carbon emissions of the process while maintaining the required quality standards. By optimizing the machining parameters, they were able to reduce the processing time by 5.84 % and carbon emissions by 6.1 %, which can significantly impact the sustainability of the manufacturing process.

Machine and process setup can be a time-consuming and complex task. One critical aspect is determining the ideal settings for a reproducible and high-quality production process. Traditional trial-and-error methods are often inadequate, costly, and time-consuming, resulting in suboptimal production processes. Therefore, many researchers have explored using the Design of Experiments (DOE) to efficiently and effectively optimize the manufacturing process. One example of the application of DOE in manufacturing is the work by Bibow et al. [19], who used a DT in injection molding to autonomously generate, execute, and validate a central composite design for three varying parameters. This approach allowed for a more efficient and precise method to optimize the production process. Another example is the work by Rauch and Pietrzyk [110], who developed a hybrid computer system to design the optimal manufacturing technology for thin steel strips. The DT technology has been applied to various manufacturing processes, such as dynamic clamping and positioning of a flexible tooling system, as proposed by Liu et al. [74]. The DT technology has the potential to impact the manufacturing industry by providing an efficient and reliable method for process optimization, reducing time and costs associated with traditional trial-and-error methods.

Path planning is a critical aspect of robotics applications as it involves determining the optimal path for a robot to follow while ensuring that it avoids collisions with obstacles in the workspace. This is particularly important in manufacturing environments where robots are commonly used to perform tasks that involve interacting with other machinery or humans. However, traditional path planning methods can be time-consuming, costly, and may not be optimal. Therefore, many researchers have explored using DT representations of robotic applications to plan the optimal path while avoiding obstacles in the workspace. Bansal et al. [16] and Khanesar et al. [62] are examples of researchers who have used a DT representation of robotic applications and a description of the final product to plan the optimal path while avoiding obstacles in the workspace. Furthermore, they used different optimization algorithms to determine the best path, such as gravitational-guided random search Khanesar et al. [62] and ant colony optimization [16].

Process planning is an essential step in manufacturing, and optimizing process parameters is key to achieving efficient and effective production. By leveraging DT technology, it is possible to develop models that accurately reflect the behavior of physical entities and use these models to optimize process parameters in real time. For example, Liu et al. [75] developed a two-step method to optimize process route and machining parameters such as feed rate, depth of cut, and spindle speed for dimensional accuracy and processing cost.

Motion control involves regulating the movement of robotic systems to achieve specific tasks. The challenge with motion control is ensuring that the movements executed by the robot are safe and reliable, particularly in collaborative settings where robots work alongside humans. DT technology can be used to develop virtual models of robotic systems and environments, which can be used to validate the safety and feasibility of robot movements. DT-based models can be used to simulate the behavior and performance of robotic systems, enabling designers and engineers to test different scenarios and configurations before implementing them in the physical world. For example, Horváth and Erdos [52] developed a gesture-based control method for multiple collaborative robots and used the virtual entity of the DT to validate the safety and feasibility of actions.

Adaptive control uses feedback mechanisms to adjust process parameters and improve performance. Identifying the optimal process parameters that guarantee stability and consistency while accounting for uncertainties and variations in the manufacturing process is one of the challenges in adaptive control. However, virtual models of manufacturing processes and environments developed in DT can serve as an information repository of data from upstream and downstream processes. For example, Zehetner et al. [145] presented a DT-based adaptive process control that links data from CAD design and the final metal sheet part to overcome uncertainty due to process and material variations.

Summary and discussion of digital twin services

We categorized DT services into *product customization*, *visualization*, *monitoring*, and *optimization*, shown in Table 4. We found that most DT services belonged are used for monitoring, optimization, and visualization. Product customization received the least attention.

Monitoring services can help by assessing manufacturing units' health and product quality. DTs can help avoid inconsistency and inefficiency in manufacturing processes by monitoring the equipment's condition and scheduling maintenance activities. Moreover, monitoring data can be used to update the DT to represent the latest status of the physical counterpart.

Model calibration and state estimation are key services to update the DT representation. Both techniques aim to calibrate model parameters to achieve the best fit between the model and physical system outputs. Our review shows that (21) papers used direct mapping of sensor data to model inputs. Some papers relied on model and data fusion techniques, and others used rule-based models for updating model parameters online. Interestingly, little emphasis was placed on state estimators by fusion of model outputs and measurement data such as Particle and Kalman filters. In the future, we expect those techniques to become more prominent for the real-time assimilation of sensor and model data.

Additionally, weight tables can become an essential tool for prioritizing which model parameters to update, e.g., highly dynamic changing parameters and parameters with a significant impact on model outputs. Future research should consider the effects of model parameters on model outputs and develop generalizable methods for selecting weights of individual model parameters.

Optimization services aim to increase production efficiency by means such as lowering cost, time, energy, and carbon emissions. For example, DTs can assist in setting up new equipment by designing automatic experiments. Also, DTs can tune the running equipment for higher quality products and lower expenses. Furthermore, DTs can help reduce carbon emissions by setting manufacturing processes to work on their optimum working points. Moreover, DTs can plan the movements of robots to remove the collision and ensure safety for collaborative robots. Finally, DTs can improve process stability and consistency by employing adaptive control. Currently, the majority of the optimization services were not applied in real-time but offline prior to the physical process. Future research should focus on creating optimization models capable of performing optimization tasks within the required time frame, and under consideration of safety conditions and the changing conditions in which the models operate.

Visualization services support manufacturing activities by creating interactive visualization of virtual entities. Further, graphical visualization techniques enable human actors to review data from manufacturing remotely through dashboards and graphs. Visualization receives a large interest from industry and research. Various tools are available for visualizing, analyzing, and presenting data such as dashboards and 3D environments. We believe that visualization methods are one of the best-developed services for use in DTs.

Product customization services can be grouped as geometric variations management, assembly sequence planning, and adaptive modeling services. DTs can assist by compensating for geometric variation during part assembly. Similarly, DTs can plan assembly sequences based on customized product specifications provided by the user. Furthermore, DTs can adapt product and process models based on variations of the physical products. The reported methods aim at serial production where data from preceding parts can be used. However, challenges to applying DTs to single-part production are less researched today. Thus, future research should consider how geometric variations management and related services can be used for preventive quality control during the manufacturing phase both in serial and single-part production.

Digital twin content

Models and data make up the basic content of a DT. DT models consume the data to create a dynamic representation of the physical entity. In the section Models, we grouped models into four primary types: geometric, physical, behavior, and rule models. Also, we described how the different model types were used in the context of unit level DTs. In the section Data and Communication Technologies, we listed data sources and types in manufacturing, summarize the different communication protocols, and highlight data storage technologies.

Models

Models reflect and facilitate human understanding of nature, society, and other issues. Modeling describes the process of abstraction i.e. the reduction of the original physical entity to represent only relevant aspects given a specific purpose [90]. Models play an integral part and act as a precondition for successful DT applications by extracting value from data. In the context of a DT we selected the term model to refer to immaterial models such as mathematical descriptions [125].

We classify models from the corpus of reviewed papers in four DT model dimensions introduced in [107] and summarize key findings in the sections (i) Geometric Models, (ii) Physical Models, (iii) Behavior Models and (iv) Rule-based Models.

Table 5
Overview of modeling techniques by model type. The specification column describes the implementation strategy. Some references implement multiple models and are thus included multiple times.

Type	Sub-type	Area	Technique	Ref.
Geometric	3D model	Robot & Environment	Manual	[51,16,87,62,52,143,117,152,46,86,85,36,127,148]
		Machine	Manual	[53,59,49,78,150,111,145,22,80,50,24,118,54,153,12,93,70,96,105,91]
		Work piece	Manual	[123,102,51,77,6,67,33]
			Computational	[141,20,23,91]
			Scanning	[77,144,152]
		Human	Manual, scanning	[52,17,86,85]
Physical	First principles	Human-robot collaboration	Kinematic/Anthropomorphic model	[17,85]
		Robot kinematics	Denavit-Hartenberg notation	[16,62,124,117,136,17,152,46,85,56]
		Robot dynamics	Lumped parameter model	[10]
			Newton-Euler/Lagrangian method	[98,143]
		Machine kinematics	(Multi-)Rigid body	[59,49,54,153,12,70,105]
		Machine dynamics	Newtonian mechanics (dynamic eq.)	[68]
		Energy consumption	Torque model	[143]
		Full machine models	Multi-domain model	[5,93,134]
			Discrete event model	[24]
		Part assembly	Finite element analysis	[102,123]
		Bending process	Finite element analysis	[49,145]
		Rolling process	Analytical	[27,50]
			Finite element analysis	[110]
		Composite manufacturing	Finite element analysis	[144]
		Thermodynamic processes	Finite volume method	[26]
			Surrogate model	[55,97]
		Material removal process	Molecular dynamics	[126]
			Mechanics of material removal	[141,134,20,23]
			Discrete element method	[104]
			Analytical	[103,150]
	Data-driven	Full machine models	Multi-domain model	[84,13,33]
		Material removal process	Neural network	[119]
			Linear regression	[22]
		Aluminum smelting	Exponential regression	[72]
		State & quality prediction	Artificial Neural Network	[108,115]
	Hybrid	Full machine models	Multi domain model	[83]
		Fused filament fabrication	Analytical & computer vision	[92]
		State & quality prediction	Exponential degradation model	[25]
			B-spline fuzzy neural network	[84]
			Support vector machine	[37]
Behavior	Flow	System interactions	Sequence diagram	[15]
			Activity diagram	[52]
		System control logic	Architectural Description Language	[19,12,105]
			PLC Input/Output model	[59,69,36,70,96]
	State	Machine & process states	Hybrid automaton	[14]
			Finite state machine	[126]
			Hidden Markov model	[98]
			Decision forest	[83,144]
			Artificial Neural Network	[73]
Rule	Learning-based	Robot control	Reinforced learning	[87]
		Computer vision	Rule-based clustering	[52]
		State & quality prediction	Time series forecasting	[89]
			Exponential degradation model	[25]
			Artificial Neural Network	[84,147,108]
			Support vector machine	[101,151,37]
			Birch algorithm	[28]
			Fuzzy rules	[73]
	Expert-based	Process transition logic	Constraint model	[36,86,77,85,124,96]
		State & Quality monitoring	Constraint model	[5,28,83,111,138,152]

Geometric models

Geometric models describe the shape, appearance, and geometry in the form of points, lines, surfaces, or bodies of physical entities using mathematical formulae. DTs primarily use 3D modeling for visualizing and animating physical entities. 3D models were reported for four types of physical entities: industrial and collaborative robots, human operators, machine tools, and products.

Industrial and collaborative robots were visualized by Bansal et al. [16], Khanesar et al. [62], Matulis and Harvey [87] using 3D representations of the robotic cell including robot manipulators and surrounding environment. Further, Malik and Bilberg [85] made a dedicated effort to detail object placement in the 3D model of a robotic cell. Additionally to visualizing the robot manipulators, Malik and Brem [86], Baskaran et al. [17], Horváth and Erdos [52] incorporated 3D rendered human models.

Manufacturing machine tools such as desktop 3D printers [53], complex machine tool systems [49,59,68,78,80,89] and individual machine components [111] were also visualized using 3D modeling.

Work pieces were further represented in 3D. For example, Liu et al. [77] used as-designed geometric workpiece models and compared those to the measured in-process geometry; Alexopoulos et al. [6] used the virtual environment to generate a training set containing images of the same part geometry under various placements and lightning conditions, and Moreno et al. [91] applied computational geometry techniques and boolean operations to display part geometry after the punching process.

Table 6
Number of papers and associated model construction methods.

Type	#
First Principles	47
Data-driven	8
Hybrid	5

Model construction for 3D geometrical models in DT is supplemented by modern product development processes in which often 3D-CAD models are created by engineers. Those models can be re-used for creating geometric models in a DT. In Table 5 we labeled this technique as manual model construction. On the other hand, to create an in-process representation of the workpiece, some papers used optical and tactical systems, such as 3D scanners or coordinate-measuring machines (labeled as scanning) and mathematical models, and computer graphic techniques.

Physical models

Physical models rely on the underlying physics to represent machines and processes. We categorize physical models into three different types: First principles, data-driven, and hybrid models. Table 6 shows the number of papers associated with first principles, data-driven and hybrid models.

First principles models require domain knowledge and describe physical phenomena by fundamental physical laws. First principles models consist of governing equations, supplementary sub-models (defining and constitutive equations), and assumptions and constraints (initial- and boundary conditions, classical constraints, and kinematic equations). First principles models were widely used within two categories: Robot-aided manufacturing and manufacturing process modeling.

In the field of robotics, first principles were used to model the kinematic behavior [16,51,62,87]. Kinematic models describe system motion (positions, velocities, and accelerations) based on geometric relationships of the system without regarding forces [48]. Most papers used the Denavit-Hartenberg notation which is a standard notation for describing the kinematic equations of serial manipulators in terms of the pose of one body with respect to another. Furthermore, kinematic models were used for defining motion constraints and connection types of selected machine components [49,59,78].

Another approach is using dynamics to describe the motions of mechanical systems due to forces. For example, Kutin et al. [68], Tong et al. [134] reported a dynamic model of a feed drive component; Park et al. [98] modeled robot dynamics using the Lagrange equations; and [10] derived differential equations from lumped parameter model of a robot manipulator considering joint flexibility. Further, [80] developed a dynamic model describing the deflection of a machine structure. Integration of the original kinematic and dynamic models within a DT setup was reported as a complex task requiring a substantial amount of work that is further challenged by semantic interoperability problems [80].

Kinematic models of robotic arms constitute many of the discovered and reviewed first principles models. Robotic arms are well suited for DT applications as the needed data for the kinematic models is available, with no need for the installation of external sensors. Furthermore, the study of robotic arm DTs can be application agnostic. This makes kinematic models of robotic arms well suited for general DT framework and architecture studies, such as [56,85,124].

First principles models are also well-suited and commonly applied for modeling manufacturing processes. We identified two common approaches: Numerical and analytical. For example, [27] described the load-deflection behavior in a straightening process by analytical models for the elastic loading, elastoplastic deformation, and elastic rebound stage. However, if analytical methods cannot solve the differential equation describing the underlying physics, approximations of these equations can be derived using numerical methods. The most frequently reported method to numerically solve differential equations in DTs is FEM. For example, [110] reported the use of FEM (1D) of deformation during rolling; [49,145] used FEM (2D) for elasto-plastic bending processes; [123] used FEM (3D) model describing product variations; and [102] used an thermo-mechanic FEM model describing manufacturing variation.

Also, we identified process models for thermodynamic and material removal processes. For example, Moretti et al. [92] used thermodynamics and conservation laws for modeling the layer contour edge for an extrusion process, and Chen et al. [26] used the heat transfer equation for modeling heat diffuses in stir welding. Different material removal models were also reported. For example, Pombo et al. [104] employed a discrete element method based on rigid particles considering contact forces between those particles in the grinding process, and Stavropoulos et al. [126] modeled material removal and phase changes for a laser material removal process using molecular dynamics.

As stated, numerical models are well suited for DT applications. The numerical model's physics- and causality-based nature makes them easier to adopt in a manufacturing setting, especially for high-fidelity models. However, high-fidelity numerical models may not always be appropriate for DT applications as fidelity comes at the price of computational cost or simulation time. To solve this problem, reduced order modeling or simplifications can be used as demonstrated by Hartmann et al. [45] and Zehetner et al. [145]. Determining model fidelity is important for organizations embarking on a DT journey, a framework for determining the required model fidelity by balancing technical constraints, organization constraints, and financial constraints is proposed by Kober et al. [64].

Data-driven models are input-output mappings based on domain-specific rules derived from data. The quantity and quality of data significantly determine their performance. Data-driven models capture both known and unknown physics without requiring expert knowledge but do not extrapolate well to cases outside of their domain [109]. For example, Lawrence et al. [72] developed a regression model for the tapping temperature in a tilt rotary furnace, and Shatagin et al. [119] described machine dynamics by a neural network model. Advanced deep learning models were utilized for characterizing machine tool condition [108], and for automated fault detection based on vibration data [115].

Data-driven models, such as machine learning models, are generally effective and highly accurate within their training range, however, unforeseen circumstances may arise that push the process parameters beyond the range of their training data. In these situations, the prediction behavior of the machine learning models is not guaranteed, this concern may hamper the adoption of machine learning models for manufacturing applications and may be the cause of the relatively small amount of machine learning based DTs found in this literature review. Furthermore, the applications found here are typically auxiliary manufacturing process optimizations such as state and health prediction, and CNC machining path optimization, as opposed to being used for direct process control.

Hybrid models combine first principles and data-driven models to overcome the limitations of both approaches. The information within first principles models can increase confidence by providing insights into the hybrid model, while the data-driven model can derive a solution if the first principles model becomes computationally unfeasible to solve and can help to uncover complex behavior not included in the first principles model. Depending on the hybrid model, first principles models and data-driven models can be arranged in parallel (the submodel outputs combined give the output of the hybrid model) or in series (the output of one submodel is used as input to the other submodel). For example, Papacharalampopoulos et al. [97] employed hybrid modeling for adaptive control, and Gaikwad et al. [37] combined a FEM model and a support vector machine model to increase the prediction fidelity of fault detection in additive manufacturing.

Behavioral models

Behavioral models describe system response mechanisms to stimuli from its environment such as events and data inputs. Flow models and state models were found as the two main sub-types of behavioral models.

Flow models of control commands and messages within a system were described using activity and sequence diagrams. For example, Bamunuarachchi et al. [15] modeled the interaction of sensing and actuation service, and various DT services through a client application interface. Also, system control logic was modeled using flow models and architectural description languages. For example, Bibow et al. [19] modeled behavior, events, and actions of an injection molding machine using the Architectural Description Language MontiArc; Janda et al. [59] emulated a CNC control kernel and described the PLC Input/Output mapping; and [69] modeled the signal response of a CNC control unit (i.e. voltage applied at the controller pins) to G-code commands.

State models characterize the internal dynamics of machine and process states. For example, Park et al. [98] used a Hidden Markov model to model the reactive control of components in a robot cell, and Balta et al. [14] developed a generic hybrid automaton of the continuous and discrete event dynamics for additive processes.

Rule-based models

Rule-based models are either extracted from historical data using learning-based techniques or are defined by domain experts. Rule-based models enable reasoning, evaluation, and autonomous decision-making within DTs [107].

Learning-based rule models were reported for robot control, computer vision applications, device state estimation, and part quality prediction. Reinforced learning-based control can act similarly to a controller in a control system and is particularly suited for controlling complex non-linear systems. For example, Matulis and Harvey [87] applied reinforcement learning for optimal control of robot motion through direct control of the servo drives and without modeling the underlying physics of the robot manipulator. Furthermore, computer vision allows the extraction of knowledge from images and videos for defining rules. For example, Horváth and Erdos [52] controlled a robot with a rule-based clustering model of different hand gestures. Further, Alexopoulos et al. [6] trained a convolutional neural network for selecting adequate picking strategies using virtual rendered parts under varying orientations and lighting conditions, and Moretti et al. [92] applied a Canny filter for monitoring part quality in additive manufacturing by comparing as-designed and in-process outer part contours. Moreover, state prediction allows forecasting device states or events based on historical knowledge. For example, Miao et al. [89] trained a multivariate time series analysis model based on probability intervals of the normal operating range of a machine tool. Other remaining useful lifetime models used an exponential degradation model [25] and a B-splines fuzzy neural network [84]. In addition, quality prediction models allow forecasting part quality using patterns in process data. For example, Pereverzev et al. [101] used force and power data as inputs to a support vector machine classifier of weld quality; Zhang et al. [147] classified product quality using an encoder artificial neural network; and Scheffel et al. [115] identified faulty time sequences in process data using a convolutional neural network. Further, Zambal et al. [144] used a random forest model to classify defect types in composite parts, and Lermer and Reich [73] used a fuzzy rule set simulation to generate augmented data as input for an artificial neural network model of product quality. A common structure of the reviewed learning-based rule models can be identified as typically consisting of a machine learning based data-driven model to enrich sensor measurements that are then passed on to a set of rules for decision making, enabling the DT based autonomous decision-making. Being typically based on machine learning models a possible challenge for the rule-based models is the inherent variance of products from upstream of the production line. While well-trained machine learning models make reliable predictions within their trained range, this is not necessarily the case for predictions based on input data outside their training range. This is an important point to consider when designing learning-based rule models. However, multiple approaches can be utilized to limit this, such as but not limited to, utilizing explainable AI methods, limiting the use case and using plentiful training data also representing rare occurrences of possible upstream deviations. However, the learning-based rule models come naturally with a toolset for mitigating the risk of unreliable predictions, the defined ruleset.

Expert-based rule models derive rules from expert and domain knowledge. Commonly, process transition logic, and state and part quality models were implemented using if-then statements i.e. constraint rules. For example, Fernández et al. [36], Malik and Bilberg [85], Malik and Brem [86] defined sequential transition of a robotic task, human tasks, and behavior for collaborative environments, e.g., if part detected then pick part, and Sonkoly et al. [124] defined rule-based collision avoidance and detour planning for an industrial robot. Other expert-based models were reported for state and quality monitoring. Based on a threshold for device or product-related metrics, a rule-based model can trigger warnings if the metrics move outside of the normal operating range. For example, Redelinghuys et al. [111] defined rules for the timing duration of various tasks and linked those rules to sensor readings for guiding diagnostics toward a possible error source.

Data and communication technologies

Communication technologies enable synchronization and transferal of data between the physical and virtual entity. The physical-to-virtual data flow can drive real-time simulation and analytics, while the opposite flow can command operations of the physical entity. The data that flows between the virtual and physical unit-level entities is collected from various sources along the manufacturing life cycle. After data collection, this primary data can be processed using adequate algorithms and ingested into a database for storage and later retrieval.

Following, we listed data sources and data formats in the section (i) Data Sources and Formats; transmission protocols to send information between systems in the section (ii) Communication Protocols; and data storage technologies in the section (iii) Database Systems and Ontology Models.

Data sources and formats

Different classifications of data sources for unit level DTs were provided. For example, Hänel et al. [44] differentiated between workpiece data, process data, technology data, machine data, and tool data. Additionally, Caesar et al. [20] distinguished workpiece data, material data, technology data (such as clamping strategy, tooling, and NC program), static machine data, and dynamic process data. Following, we summarized data sources and formats by five primary process phases: design and engineering, manufacturing, product quality, and virtually simulated data.

Design and engineering data contains all data related to representations of a product and process. Design and engineering data primarily consists of data that is fixed or infrequently changed after handover to manufacturing. Examples of design and engineering data are 3D geometry data (e.g. CAD), process planning data (e.g. CAM), bill of materials, workpiece and material information, and rudimentary device properties [111]. This data is created before manufacturing and does not originate from the machine tool. The data represents the as-designed values, such as feeds, speeds, workpiece geometry, material properties that control the output of the manufacturing process, and information on the quality requirements of the final output. After processing, a comparison of theoretical as-designed and actual as-manufactured information can be used to evaluate the output of the manufacturing process.

The most prominent example of design and engineering data reported in the reviewed papers was 3D geometry data. 3D geometry data were described using various file formats. For example, Alexopoulos et al. [6] exported the product model as the Standard Tessellation Language (STL) file format, and Miao et al. [89] used the Wavefront Object file format (also known as OBJ file extension) to represent a machine tool. STL files represent a geometry using only triangles with no texture or color included. Thus they have a small size, while the OBJ file format is more accurate in resolution and textural appearance but considerably larger in file size. For an interactive representation and configuration of 3D objects and scenes, XML [91], and XML-based formats such as X3D [127] and Unified Robot Description Format (URDF) [136] were reported. URDF files can describe a system's kinematics and are typically used in the modeling and simulation of robots. In the previous section, it was described that Denavit-Hartenberg parameters could be used to represent the kinematics of a system; these parameters can be directly translated into a URDF file by performing linear transformations. Furthermore, Redelinghuys et al. [111], Malik and Bilberg [85] converted CAD models of the physical entity into the Jupiter Tessellation format, an ISO-standardized 3D graph scene exchange format. The Jupiter Tessellation format is lightweight compared to a CAD file and has the advantage of fast loading and manipulation time of large numbers of 3D components. Hoebert et al. [51] used another file format for efficient transmission and loading of 3D scenes called the Graphics Language Transmission Format.

Manufacturing data contains all data created during actual production, i.e., machine control traces and external sensor data. Machine control traces can be collected from machine PLCs to provide insight into machine motion and status. In addition, specifically designed sensors attached externally to the machine control system can capture advanced insights into physical phenomena such as cutting forces, chatter, and temperature distributions. The main type of manufacturing data collected from unit-level entities was status and multidimensional time series data [22,25,84,89].

Product quality data characterizes how well outputs from the unit processes, i.e. parts or products, satisfy requirements specified in the engineering and design phase. Prominent technologies to measure product-quality attributes are coordinate measuring machines, 3D scanners, and computer tomography systems. For example, Söderberg et al. [123] measured 3D point clouds of individual components and stored deviation data from nominal at defined inspection nodes. The file size of quality measurements increases with the required resolution and tolerance requirements of the product. Additionally, it can be practical to store manufacturing and quality data in the same place. This can be challenging due to the high volume and variety of data. To handle and store the high data volume from a variety of sources, Zambal et al. [144], Caesar et al. [20] relied on the HDF5 file format, and Liu et al. [74] used a XML description.

Virtual data can be generated during all process phases by services and applications of the DTs system such as simulation and analysis. A prominent example is virtual sensing where process data is used to estimate parameters for which direct measurements on the physical system are not feasible. Ideally, virtually generated data is captured and stored alongside the physical entity data. For example, Zhao et al. [150] stored simulation results of a DT service for energy optimization, manufacturing data, and engineering data.

Communication protocols

For sending and receiving data, communication protocols are required. Commonly, communication protocols are structured in layers. We grouped the technical implementations used by the reviewed papers in the physical, data link, and transport layers. The physical layer provides the electrical/mechanical means to transmit raw bit streams, the data link layer transfers data frames between nodes through the physical layer, and the transport layer ensures the data is delivered to the correct process.

Table 7 lists the platform-independent communication protocol for sending data and control commands between the virtual and physical entities of reviewed unit level DTs. Note that besides platform-independent protocols, the link between the physical and virtual entities must often be established via commercial systems developed by the producer of the machines and sensors.

OPC Unified Architecture (OPC-UA) is a connectivity framework standardized in IEC 62541, specifically designed for the manufacturing industry. OPC-UA scales well across machine types and provides a range of capabilities such as support for bi-directional data exchange. Further, OPC-UA supplies a library of generic, semantic information models for various physical devices. Third, OPC-UA allows instantiating these generic device models to particular devices providing functionality, e.g., generic functions to move machine axes applicable to all CNC machines that support OPC-UA. For messaging, OPC-UA supports both publish/subscribe pattern (server continuously publishes status) and a request/response pattern (server broadcasts status only when requested).

Message Queuing Telemetry Transport (MQTT) is another open connectivity standard commonly maintained by OASIS. MQTT supports bi-directional communication for DTs. Compared to OPC-UA, MQTT is a lightweight protocol that only supports the publish/subscribe model. The lightweight is achieved using a message broker, which receives information from the client(s) and publishes it to subscribing client(s). For example, a physical CNC machine tool can publish axis positions through a broker. The broker assigns the axis position information a specific address that multiple virtual entities (clients) can subscribe to. For example, Aivaliotis et al. [5] used Eclipse Mosquitto, an open-source message broker based on the MQTT protocol, to retrieve data from an MQTT-enabled sensor.

MTConnect is a connectivity framework standardized in ANSI/MTC1.4–2018. MTConnect supports retrieval of process information from NC machine tools by process monitoring while providing a common, standardized vocabulary for generated data. The centerpiece of MTConnect is agents, which connect to a machine tool and store monitoring data in a buffer to publish information upon request to a client. Tong et al. [134] highlighted the suitability of MTConnect protocol for data fusion and transmission due to low network delays, which in some cases are critical for real-time applications of DTs. However, MTConnect intrinsically supports read-only and thus does not support bi-directional data flow as DTs require. To overcome this limitation, Shahriar et al. [118] proposed MTComm, an extension of MTConnect, to monitor and command operations over the network.

Ethernet is the most commonly used technology for connecting machine tools to the industrial network. Depending on real-time performance requirements, modifications of Ethernet exist that rely on different software and hardware stacks. We identified three types of Ethernet modifications: Profinet [112], Sercos-III [35,112] and EtherCAT [139,140,147]. Apart from a wired connection, wireless local area network technologies and the wireless broadband telecommunication standard such as LTE were reported by a minority of papers.

Connectivity protocols usually transfer data and control commands between a physical and virtual entity (inter-communication). Apart from inter-communication, the intra-communication of models and services within the virtual entity requires protocols for

Table 7
Communication protocol stacks found in the corpus of DT literature that were used to engineer unit level DTs.

Layer	Name	Reference
Data type	XML	[53,143,127,118,150,84,67]
	JSON	[51,56,140,119]
Application	OPC-UA	[56,89,25,12,50,36,105,98,149,84,67,139,111,23,19,49,111,23,19,49,153]
	MQTT	[5,6,56,139,141]
	HTTP	[148,6,53,127,152]
	MTConnect	[118,134,53,23,23]
Transport	TCP/IP	[80,91,115,53,28,44,20,51,111,19,112,143,16,111,19,143,119,92,86,114,14,144,152,153]
	UDP	[53]
	ZeroMQ	[46]
Physical / Data Link	Ethernet	[147,80,140,91,139,35,112,112,153]
	Modbus	[24,72,138,15,22,153]
	WLAN	[140,49,49]
	LTE	[140]

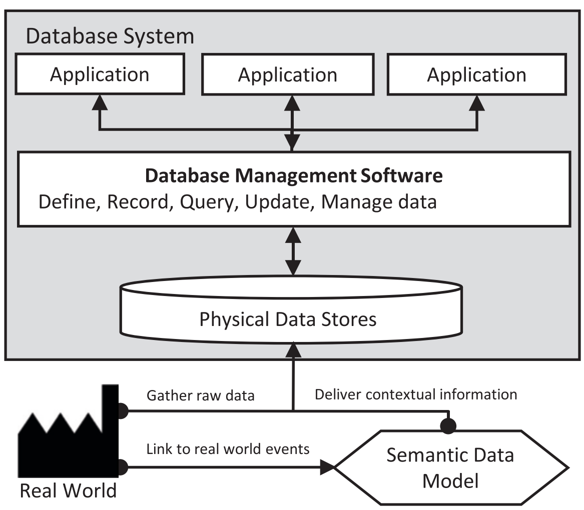


Fig. 7. Database system consisting of application interfaces, database management software, and database storage. Raw data is ingested from the real world into physical data stores. The data stores use symbols defining real-world assets, events, etc. To relate those symbols and the real world, semantic data models independent of the logical database structure can be used [71].

exchanging data and information. For example, Arkouli et al. [10], Khanesar et al. [62] used the Remote Desktop Service Application Programming Interface to communicate between DT services and simulation models, and Janda et al. [59] relied on the Windows COM interface to communicate between virtual numerical control models and simulation models of the machine tool.

Database systems and ontology models

With communication protocols to exchange data, monitoring data from physical entities and simulation data from virtual entities can be stored using database technologies. Fig. 7 shows the typical components of a database system: applications, database management software, and physical data storage. A database is typically populated with raw data collected from a physical entity. Database management software enables users and applications to store and access data elements in the physical database. The logical data structure, i.e., how the database stores the data, classifies database systems typically as relational and non-relational. The review indicates that most papers (74) did not use a database system.

Relational databases typically contain data structured in tables and use the Structured Query Language (SQL) to interact with the data. Interactions may involve adding new records to an existing table. Six papers relied on SQL databases such as open-source management systems MySQL and PostgreSQL. For example, Cai et al. [22] stored machine data, sensor data, and the machine status of a milling machine in a PostgreSQL database. The use of relational databases to manage DT data has several advantages. First, relational databases provide a way to organize and structure data, making it easier to store and retrieve information. Second, relational databases allow for efficient querying of data, which is essential for analyzing and monitoring DTs. Third, relational databases provide a level of data security and integrity that is essential for critical systems. However, the use of relational databases for DTs also has some limitations. First, relational databases may not be suitable for managing unstructured data, such as images or videos, which are becoming increasingly important in many industries. Second, relational databases may not be suitable for real-time applications that require fast data processing and analysis. In such cases, non-relational databases may be more suitable.

Non-relational databases (also called NoSQL) store data provided in a non-tabular format. NoSQL databases provide flexibility to digest information of various kinds and formats side by side and do not rely on a predefined schema. Eight papers used NoSQL database systems such as HBase, MongoDB, and proprietary systems of the 3DExperience software. For example, Xi et al. [141] stored cutting force data and machine data from two milling machines in a NoSQL time-series database. One of the most significant advantages of NoSQL databases for DTs is their ability to handle unstructured, semi-structured, and structured data structures. NoSQL databases can manage streaming data, handle high-volume writes, and allow fast querying. This can be essential for DTs that generate large volumes of data and require real-time analytic services. However, NoSQL databases can be more challenging to set up and maintain compared to traditional relational databases. Overall, NoSQL databases offer several benefits for managing and analyzing DT data, especially for applications that require scalability, flexibility, and performance. As the demand for scalable, flexible, and cost-effective data management solutions continues to grow, organizations increasingly turn to cloud technologies to supplement or replace traditional database systems such as SQL and NoSQL.

Cloud technologies such as cloud storage and cloud computing can help scale DTs across whole companies without owning sufficient in-house computing capabilities while reducing acquisition and maintenance costs and providing greater accessibility and potential for remote collaboration. However, there are several challenges associated with cloud-based DTs. Data security may be one of the most critical challenges. Cloud-based DTs must be designed with security in mind to prevent unauthorized access to sensitive data. Another challenge is the latency associated with cloud-based DTs. To date, commercial applications such as Amazon Web Services and OpenWhisk cloud platforms reportedly lack the latency and guarantees for real-time analysis and control [124]. In conclusion, cloud technologies offer many benefits for DTs, including scalability, accessibility, and cost-effectiveness. However, organizations must carefully consider the potential challenges associated with cloud-based DTs, such as data security and latency, and design their systems accordingly.

Semantic data models (also called ontologies) define terminology to explicitly describe data types and relationships between data types and data properties linked to physical entities [143]. Using ontologies, raw source data can be transformed into semantically enriched data. Semantically enriched data encapsulates an explicit connotation; thus, applications and machines can automatically use this information [150]. Typically, ontology models are structured in hierarchical levels. At the highest level, basic ontology models such as [1] define terms and relationships in an abstract (general) manner. Mid-level ontologies bridge abstract top-level definitions and particular definitions in domain ontologies, e.g., process ontologies and machine ontologies. Finally, application-level ontologies adopt whole or parts of existing ontology models to specific use cases. Some manufacturing-related domain ontologies are published as open references to guide practitioners into applying, extending, and reusing existing ontologies [7,65,38].

We observed the use and adoption of ontology models for engineering DTs. For example, Shahriar et al. [118] extended the MTConnect ontology model to include 3D representations of machine tools; Kubota et al. [67] developed an information model structure using the OPC-UA ontology description; Hoebert et al. [51] incorporated description of spatial information from the manufacturing entity with the existing BREP ontology; and Bamunuarachchi et al. [15] extended the existing core ontology SOSA and domain ontology SSN to include software elements. The examples mentioned in the paragraph demonstrate the diverse ways in which ontology models can be used in DT engineering and can help ensure interoperability and consistency among different DT systems. Overall, these examples highlight the potential benefits of using ontology models in DT engineering, such as improving interoperability, accuracy, and visualization capabilities. However, there are also challenges associated with ontology modeling, such as the need for domain-specific expertise and the potential for model complexity.

Various tools and frameworks can be used to create and operate ontology-based DTs. For example, Yan et al. [143], Zhao et al. [150] used the Protege Editor, and Hoebert et al. [51] used the software tool Rosetta to create an ontological description of a machine tool. In addition, the Protege plugin OntoSTEP can transform design information into ontology models in text-based formats such as XML and Web Ontology Language. For example, Lu and Xu [82] transformed STEP-NC information into an ontology in Web Ontology Language, and Moreno et al. [91] converted G-Code instructions into a machine-independent XML format. Moreover, Yan et al. [143], Zhao et al. [150] applied the application-level ontologies by parsing information using the semantic web framework Apache Jena. Ontology models are increasingly being used to engineer DTs. Ontology editors and semantic web frameworks provide the necessary tools and functionalities for creating and operating ontology-based DTs. These tools and frameworks can help improve the interoperability, accuracy, and reuse of digital manufacturing data. While ontology editors and semantic web frameworks provide valuable tools for creating ontology models, there are also challenges associated with their use. For example, creating ontology models requires domain-specific expertise and can be time-consuming and resource-intensive. Additionally, ontology models can become overly complex and difficult to maintain, which can hinder their interoperability and usefulness. Finally, ensuring the consistency and accuracy of ontology models can be challenging, especially when integrating data from different sources or dealing with evolving domain knowledge.

Summary and discussion of digital twin content

The core content of a DT is models and data for characterizing the physical entity. The engineering process of adequate models and acquisition of a robust data foundation requires the most significant effort toward engineering DTs. This claim is supported by the observation that the majority of papers placed their primary focus on model engineering and data-related tasks.

Models have the purpose of accurately reflecting a physical entity such as a machine tool or manufacturing process. However, DT models are always a simplification of the actual physical entity. The modeling scope (also known as twinning scope) defines the comprehensiveness, i.e., the degree to which the DT captures individual components and processes, and accuracy, i.e., the error between model outputs and the physical system, of the DT. The more limited the twinning scope, the less accurate and comprehensive the DT will be. In practical terms, this means that DTs may not be suitable for all applications and use cases. For instance, if the system being modeled is highly complex and involves numerous interactions and dependencies that are difficult to capture and model accurately, the twinning scope may be limited, leading to a less accurate DT. Additionally, if the data available to create the DT is incomplete or unreliable, this may further limit the twinning scope and reduce the accuracy of the DT. Therefore, it is important to carefully consider the twinning scope when developing and applying DTs to real-world systems. Frameworks such as [64] can be used to evaluate and determine the required model twinning scope. It is essential to understand the limitations and uncertainties of the DT and to use the DT as a tool for decision support rather than as a definitive predictor of outcomes. By doing so, we can take advantage of the benefits of DTs while acknowledging their limitations and avoiding potential risks.

Different model types with particular foci exist. We classified those model types as geometric, physical, behavioral, and rule-based models. The majority of papers used geometric (52) and physical models (60). Geometric models were typically used in 3D simulation environments. Technologies such as extended and virtual reality added the element of interactivity to 3D simulations that can be used for training, safety, and ergonomic assessment.

Physical models were grouped into three types: *first principles*, *data-driven*, and *hybrid* models. Of those three types, first principles models were adopted most frequently (47). Different first principles modeling techniques specialized in describing particular physical phenomena were used such as kinematic and dynamic modeling of machines and robots, and analytical and numerical FEM models of manufacturing processes. In particular FEM based DT models were not able to satisfy required response times for online optimization of manufacturing processes [49,145]. Further, data-driven models can exhibit lower response times. We identified data-driven models for on-line applications such as prediction of machine state and health [108,115] or material removal [22,119]. The main downsides of data-driven model is the lack of generalizability across applications or to situations outside of their training data range. Finally, hybrid models combine first principles and data-driven models to achieve generalizability, fidelity, and timely response. However, we found that only a minority of DTs (5) relied on hybrid models. The almost complete absence of hybrid models for unit level DTs indicates a potential research direction that warrants further investigation. Furthermore, less than a third of papers reported behavioral (16) and rule-based models (24). Insights and expert knowledge of physical phenomena are required such as machine tool statics, process dynamics, and system behavior, to create adequate behavioral and rule-based models of single production units. However, we observed a lack of required information. This information deficit may result from the fact that the required information resides with the original equipment manufacturer creating information islands between machine tool builders and users [140]. Thus, future research needs to support creating standard-based, interoperable models, and facilitate improved information and model exchange between original equipment manufacturers and machine tools users. We expect a growing use of behavioral and rule-based models with increasing availability of information and insights into machine tool systems.

Data and communication protocols are key technologies for engineering DTs. Data is required to update model parameters and execute models. Communication protocols enable data transfer between physical and virtual entities.

A variety of data formats, data sources, and communication protocols exist. We found that DTs consume data from various sources across the manufacturing life cycle. Primary sources are design and engineering data, 3D geometry data, manufacturing data, product quality data, and simulated data. Communication protocols such as OPC-UA, MTConnect, and MQTT experience a growing adoption in latest generation machine tools, and support fundamental functionality of DTs such as acquiring data and sending commands. However, most legacy machines do not intrinsically support those communication protocols. Absent of support lead to the adoption of external sensors and acquisition equipment which we detailed in the next section Digital Twin Deployment. Naturally, manufacturers will replace a large number of those machine tools in the coming decade. Thus, we expect a growing number of machines to support native access to monitoring data through mentioned protocols. Such a development can result in significant growth of unit level DTs in an industrial environment.

Furthermore, there was little discussion on data storage technologies. A potential reason is the lab-scale nature of most studies, where the volume of data is limited, and there is little focus on long-term data storage (or retrieval). However, for advancing the use of DTs in manufacturing industries, such aspects are critical. Even more so, with a focus on connected, digital factories where there will be a need to store and process large volumes of data.

Moreover, the main shortcoming of today's ontology models is the need for agreement on terminology and industrial standards across industries and domains. To overcome this, the Industrial Ontologies Foundry [57] attempts standardization by organizing ontology models hierarchically, and the H2020 CSA project [43] aims to standardize the documentation of manufacturing data. While a minority of papers adopted existing ontologies, the majority did not use an ontology model making it difficult to share and reuse those DTs.

Digital twin deployment

We termed the activity of putting models and data into effective action as DT deployment. DT deployment requires hardware components and software tools. In the section Manufacturing Domains and System Types, we listed and categorized the physical entities, i.e., machine tools and manufacturing devices, that DTs were reported for, and describe hardware components, i.e., sensors and control systems. Then, in the section Software Tools for Engineering Digital Twins, we listed and categorized software tools and describe the usage of those tools in the context of DTs.

Manufacturing domains and system types

Unit level DTs were reported for different manufacturing domains, e.g., material separation, and manufacturing subfields, e.g., milling machine. Fig. 8 shows a tree map displaying manufacturing domains and manufacturing subfields. The treemap is divided into regions displaying the manufacturing domain. Each region is divided again by the manufacturing subfields. The proportions of the rectangles correspond to the proportion of a specific domain /subfield of the total number of unit-level DTs found. As seen from Fig. 8, the majority of DTs were reported for the manufacturing domains separation (34), advanced robotics (23), and additive manufacturing (12). Within those three domains, the most prominent manufacturing subfields are milling machine tools (21), industrial (9), and collaborative (9) robots, followed by material extrusion processes (6). Average attention was given to bending machine tools (6), injection molding machines (4), welding (3), and grinding machines (3). Less prominent examples include subfields such as hot rolling, composite assembly, plotting, and laser cutting, with less than three DTs reported respectively.

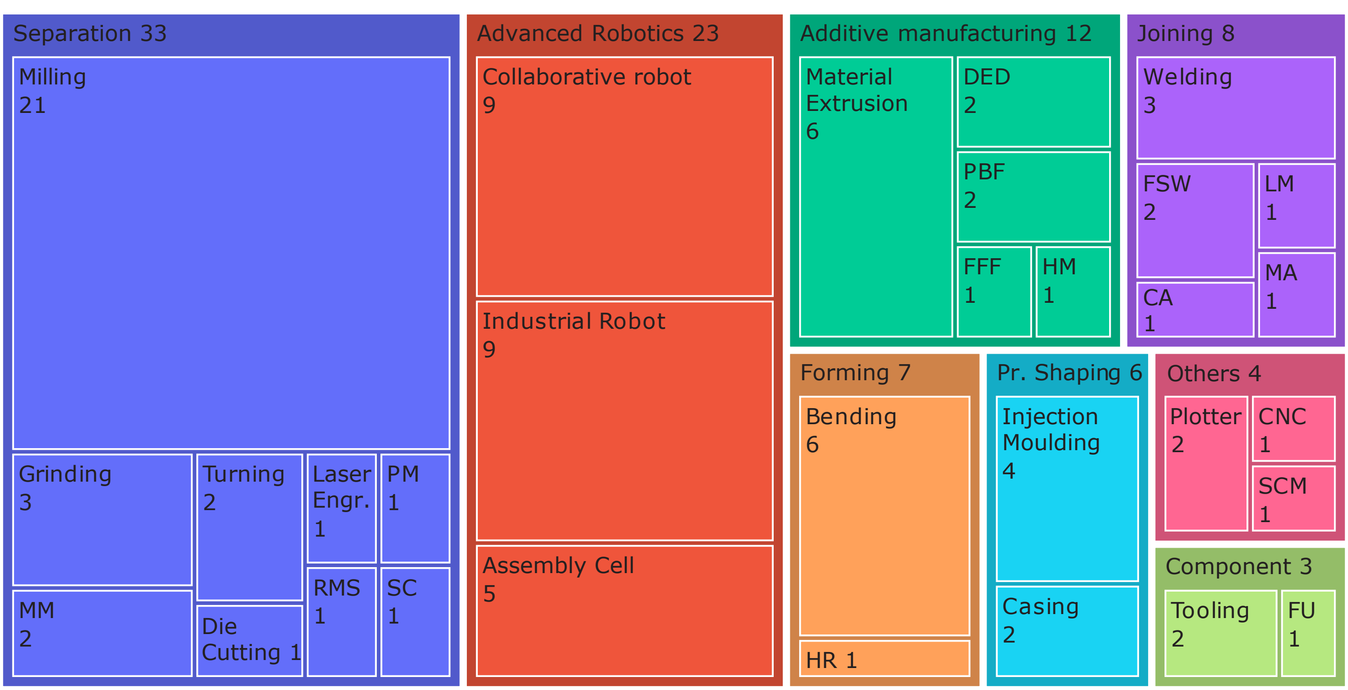


Fig. 8. Treemap quanifying the number of DTs deployed by manufacturing domain and manufacturing subfields as specified in [40]. In addition to [40], we include additive manufacturing and advanced robotic applications. *Abbreviations: Composite Assembly (CA), Direct Energy Deposition (DED), Friction Stir Welding (FSW), Fused Filament Fabrication (FFF), Fixture Unit (FU), Hot Rolling (HR), Hybrid Manufacturing (HM), Micro Manufacturing (MM), Melt Adhesive Machine (MA), Layered Manufacturing (LM), Powder Bed Fusion (PBF), Punching Machine (PM), Reconfigurable manufacturing systems (RMS), Semiconductor manufacturing (SCM), Stone Cutting (SC).*

Moreover, DTs can be differentiated by the level of openness of the physical entity into closed, open, and hybrid systems [31]. Closed systems rely on vendor-specific software tools for interaction with the control unit. Open systems intrinsically support the deployment of DTs, whereas closed and hybrid systems do not. Finally, hybrid systems are based on a closed system equipped with external equipment to expose the necessary data and control functionality toward the deployment of DTs. We summarized information on the system types and discuss the main differences in the sections (i) Closed Systems, (ii) Open Systems and (iii) Hybrid Systems.

Closed systems

Most computer numerical control systems today are characterized as closed systems, i.e., a closed control system architecture that cannot be easily accessed and freely modified by the user. Thus, collecting data and sending control commands is challenging.

The vendor usually supplies commercial data acquisition software and simulation tools to establish the physical-to-virtual connection in a closed system. For example, Caesar et al. [20], Hänel et al. [44] connected to a Heidenhain NC system using the proprietary software tool TNC Scope. Further, Angrish et al. [9] engineered a DT of an Electron Beam Melting 3D printer by relying on a vendor-specific data format through which export of the data was available only after each build job. While vendor-specific software can have advantages such as improved compatibility and functionality, several challenges can arise when using vendor-specific software to develop DTs. One challenge is the limited compatibility of vendor-specific software. While this type of software can work particularly well on the intended system, this can limit the interoperability and integration with other software and hardware. Also, migration from one vendor to another vendor or platform can be challenging. Furthermore, vendor-specific software can cause a lack of flexibility as it is designed for a specific purpose limiting customization options, which can be problematic for creating DTs that may have unique needs not supported by the vendor's software. Access to machines and processing data at adequate sampling rates for representing process dynamics is often impossible for closed systems. For example, [153] reported sampling rates of 50 Hz; Cao et al. [23], Zhao et al. [149] acquired data at rates of 100 Hz via direct connection to a Siemens NC unit; and Cai et al. [22] only collected static and slowly changing data (e.g., coolant level, tool number, machine status). Limited access to high-frequency data can significantly impact the accuracy and effectiveness of DT models. Certain physical phenomena cannot be captured using low-frequency data, making it difficult to model the physical object accurately. Also, without real-time data, decision-making may be based on outdated or incomplete information causing performance deficiencies. Overall, access to high-frequency data can be critical for developing and maintaining accurate DTs but data frequency needs to be evaluated based on the intended use case of the DT.

Most authors conceptualized the virtual-to-physical connection or stated that the virtual-to-physical connection is future work such as [139,149]. The limiting factors were stated to be the closed NC controller lacking interfaces and inadequate sensorization of the machine tools. Only a minority of publications established virtual-to-physical feedback and were able to command the physical entity by the virtual entity. For example, Hänel et al. [44] described a bi-directional data exchange between the control system and a data server. The purpose of a DT is to create a virtual replica of a physical entity in order to simulate and optimize its performance. However, without a virtual-to-physical feedback loop, any optimizations made by the DT may not be reflected in the physical asset's behavior. The current lack of virtual-to-physical feedback can be the result of several reasons such as the cost and complexity of adjusting the existing physical system, concerns about the accuracy of the model causing reluctance to integrate the feedback into the system, and implementations where it is sufficient to use the DT to simulate and optimize performance without directly influencing the physical asset. Only in the last case, the lack of virtual-to-physical feedback may not be seen as a significant limitation of the DT.

Open systems

Open systems allow extended access to the control architecture and do not rely on vendor-specific protocols. Instead, an open system is based on open communication protocols, accessible programmable logic control units, and adequate sensors. Often, open systems are built in a laboratory environment to demonstrate DTs. By building open systems with the purpose to demonstrate DTs, authors neglect the complexity of deploying DTs to industrial machine tools, such as limited access to command the physical entity and challenges in acquiring adequate data.

For example, Matulis and Harvey [87] built an open-source robotic arm using 3D printed components; Moretti et al. [92] built a Fused Filament Fabrication machine prototype; and López-Estrada et al. [80] built a six degree of freedom micro-cutting machine tool.

For controlling the physical entity by commands sent from the virtual entity, Angrish et al. [9] implemented a direct feedback of nominal deviation between commanded and real axes positions of a Makerbot 3D printer. Additionally, López-Estrada et al. [80] transformed outputs of the inverse kinematic model to machine-readable ISO code that was sent to the machine tool; and Scheffel et al. [115] used information from the simulation model to interrupt the process when defective patterns were detected.

Note, that robotic systems have a high level of openness. Industrial and collaborative robots can output sensor data such as joint rotational displacement through built-in encoders, and receive feedback commands from the virtual entity to control the robot movement through suitable interfaces [5,56]. These characteristics make robotic systems a prime candidate for deploying DTs in an industrial environment.

To summarize, the open system reported in the papers relied on hardware components with support for open communication protocols. Moreover, those systems integrated sensors selected specifically to provide adequate inputs to the physical control unit and drive the models in the virtual entity of the DTs.

Hybrid systems

Hybrid systems are based on closed systems that were equipped with external instrumentation to enable the deployment of DTs. Several authors retrofitted legacy machines with sensor technology to make those systems DT-ready [22,83,105,143,150]. Sensor fusion can increase the reliability of models and underlying data. For example, Roy et al. [114] integrated multiple sensors in a friction stir welding machine to monitor the machine tool state, and Luo et al. [84] combined temperature and vibration measurements for monitoring a ball screw drive. The integration of external sensors into legacy machines can be viable to make them DT-ready. However, retrofitting machines with sensor technologies can be a challenging and time-consuming process, requiring careful consideration of factors such as sensor placement, data processing, and communication protocols. Further research may lead to more thorough and efficient methods for developing hybrid systems, which could in turn promote the utilization of DTs in closed systems. We believe, that with an improved understanding of sensor requirements an increasing number of machine builders will begin integration of sensors off the shelf in new generations of machine tools, rendering hybrid systems unnecessary in the long-term perspective.

Some DTs applications reported the integration of robotic systems with additional sensors to gain insights into the environment of the robot, to virtualize humans performing specific tasks, and to track objects in the working area of the robot. For example, scholars used object and body tracking systems such as the Microsoft Kinect sensor [86], the Perception Neuron Pro [46], and traditional camera-based vision systems [127]. Integration of robotic systems with additional sensors may be a promising avenue for DT applications that require access to the system's environment. Through the acquisition of environmental data, the performance of the robot can be optimized, while the risk of collisions can be minimized. Moreover, the ability to virtualize human operators engaged in specific tasks and track objects within the robot's work area could significantly enhance the efficacy of human-robot collaboration across a wide range of domains. In contrast to equipping closed systems with additional sensors, in the case of robotics this trend may only be in the beginning and continued research can refine these techniques and ensure their safety and efficiency in practice.

The majority of the hybrid systems did not implement a virtual-to-physical connection. For example, Zhao et al. [151] proposed a self-adaption of machining parameters using real-time data and gradient descent but only conceptualized virtual-to-physical feedback. Similarly, Chhetri et al. [28], Reisch et al. [112] implemented multi-sensor systems for monitoring but lacked feedback to the physical entities, mainly because those systems' control units are not open. A rudimentary virtual-to-physical connection was demonstrated in a few papers. For example, Tong et al. [134] discussed a contour error simulation to provide feedback on an optimized trajectory signal to the feed drives. However, they applied the compensation to optimize the tool path offline and produce the part Second Time Right. Further, Tammaro et al. [127] controlled robot movement through a user interface for setting joint angles, velocity, and acceleration without supporting real-time feedback. The lack of a virtual-to-physical connection is a significant limitation of the DT implementations. Several challenges may result in a missing or only rudimentary implementation of the closed feedback loop such as the incompatibility of the machine's control unit to receive feedback control that cannot be resolved by adding additional sensors, the performance of models that cannot provide feedback within the required time frame, and the lack of standards and protocols for interoperability between different systems impeding integration of the virtual and physical entity. As a result, the development of effective virtual-to-physical connections remains an active area of research and development in the DT community.

Twinning rate

The twinning rate, also known as update frequency, is a metric quantifying the synchronization rate between a physical and virtual entity, i.e., the time required for a change to propagate from the virtual to the physical entity and vice versa. The twinning rate is an important design and operating criterion for DTs, because it affects the accuracy and usefulness of the DT as a tool for monitoring, predicting, and optimizing the performance of the physical entity [79,95]. Both mechanisms to establish the physical-to-virtual and virtual-to-physical connection were elaborated in the sections (i) Closed Systems and (iii) Hybrid Systems. As illustrated, the majority of publications focused on the physical-to-virtual connection, and few considered the virtual-to-physical connection. Due to the lack of focus on the virtual-to-physical connection, the following paragraphs characterize the twinning rate by the findings on physical-to-virtual connection. We found that the majority of publications did not differentiate between data sampling frequency and the frequency at which the physical-to-virtual twinning occurs The sampling rate determines the granularity and frequency of data collected from the physical entity, while the twinning rate determines how frequently the data is used to update the DT model structure and parameters [4,61]. The twinning rate can be measured in different ways depending on the type of data being collected and the frequency of updates required for a specific application. We found three common methods for updating the DT:

- **Continuous updates:** The DT is updated continuously in real-time, using data from sensors and other sources that stream data continuously.
- **Event-based updates:** The DT is updated in response to specific events or triggers, such as a change in sensor readings, or the finalization of a process step.
- **Time-based updates:** The DT is updated on a regular time interval such as every minute, hour, or day.

While 40 out of the 96 publications did not implement a full twinning cycle or specify the twinning rate, most publications (47) reported continuous DT updates. Of those, 25 only described the twinning rate as being real-time. In general, this indicates that changes in the physical entity are immediately reflected in the virtual entity. However, the definition of real-time can vary depending on the context and the specific requirements of the system. For example, in some applications, a delay of a few milliseconds may be considered acceptable, while in other applications, even a delay of a fraction of a millisecond may be unacceptable. Moreover, achieving a real-time twinning rate can be challenging due to factors such as the speed and reliability of communication between the physical and virtual entities, the complexity of the models used in the virtual entity, and the computational resources available for updating the virtual entity. Besides continuous methods, eight publications used event-based twinning methods. For example, Söderberg et al. [123] synchronized the virtual and physical product entity after every quality inspection, and Park et al. [98] updated the DT for sensor value changes. Event-based updates can be a potential solution to decrease computational cost, reduce communication bandwidth, and improve real-time responsiveness of the DT. Event-based methods only update the virtual entity when a relevant event occurs, reducing the computational cost compared to continuous methods. This also reduces the amount of data that needs to be exchanged between the physical entity and virtual entity, lowering the required communication bandwidth and possibly increasing the responsiveness of the virtual entity. Only two publications used time-based updates. Time-based updates can provide a simple, predictable, and robust method for twinning physical entities, where real-time responsiveness is not critical. They may be particularly applicable to reflect the degradation of physical components, to monitor the part quality of products and processes over time, or to track the location and status of physical entities. For example, Lawrence et al. [72] updated the virtual entity of an aluminum furnace every minute, and Aivaliotis et al. [5] predicted the remaining useful life of machinery equipment using daily updates of model parameters.

Software tools for engineering digital twins

We identified three types of software tools and summarized those in the sections (i) Engineering Software Tools, (ii) Computation and Machine Learning Tools and (iii) Visualization Software for implementing DTs. Table 8 lists software tools grouped by the three categories and provides references to related papers.

Engineering software tools

Following, we reported industrial automation, computer-aided (CAD/CAM), and engineering systems modeling & simulation software tools.

Industrial automation software can be used to simulate and test control system and PLC program behavior and is commonly supplied by the control unit manufacturer. Those software tools typically support soft- and hardware-in-the-loop simulation. For example, the Siemens TIA portal can connect to control units of the Siemens SIMATIC PLC series and grant access to data from connected devices. Furthermore, the TIA portal targets the simulation of automation systems using software-in-the-loop by emulating the controller and hardware-in-the-loop with a physical controller

Table 8
Software identified from the corpus of DT literature grouped into the three domains: Engineering software, computation and machine learning tools, and visualization software.

Domain	Tools	Description	Ref.
Engineering software	TIA portal, SIMIT platform, Sinumerik	Automation software for virtual commissioning of software and hardware, virtual training, etc.	[105,59,36,12,96,59]
	SimulAVR, TwinCAT	Simulation software for specific controller families	[69,147,12,96]
	NX, Solidworks, Catia, Inventor, SurfCAM	CAD/CAM-software tools for design, manufacturing and engineering analysis	[22,136,78,46,93,86,80,86]
	Moldflow	Computational Fluid Dynamics software for plastic injection molding	[55]
	MSC Marc, Abaqus	Finite element analysis software for nonlinear material behavior	[49,102]
	Modelica, Dymola	Model based system engineering language and tools	[84,46,80,5,98,10]
	Mechatronic Concept Designer	Software for 3D Modeling and multibody physics of machine tools and mechatronic systems	[59,105,96,59]
	Tecnomatix PS, Delmia	Development, simulation and optimization for manufacturing processes and shopfloors	[86,111,46,80,17,86]
	ROS, ABB RobotStudio	Set of software libraries and tools to build robot applications	[143,36,16,17,117,62]
Computation and machine learning tools	Matlab, Simulink	Programming, and numeric computing tools used to analyze data, develop algorithms, and create models. Simulink offers a graphical programming environment.	[92,143,25,136,102,93,80,114,68,13,33,10,62]
	TensorFlow	Free and open-source software library for machine learning with focus on deep neural networks	[87,147]
	Python	High-level programming language used in scientific computing, artificial intelligence, web applications, etc.	[55,6,50,16,115,104,28]
Visualization software	Unity, FlexSim, Gazebo, RViz, Technomatix PS	3D simulation engines for creating realistic representation of physical asset	[93,46,148,87,78,16,86,111,143]
	X3DOM, BabylonJS, WebGL	Web-based visualization frameworks for developing and running visualizations on the web	[127,51,56]

connected using the Siemens-specific tool Simit. Qi and Park [105] used the TIA portal and Simit software for PLC modeling, programming, and mapping of PLC signals using client-server communication between a physical and virtual entity. Further, Janda et al. [59] compared the automation tools Sinumeriks Virtual Numerical Control Kernel to emulate numerical control unit behavior and Mechatronic Concept Designer for hardware-in-the-loop simulation.

Computer Aided software tools can be used to describe geometric and kinematic relations of a machine tool and its mechanical components using CAD software. Typical CAD applications include Siemens NX, Solidworks, Catia, and Inventor. In addition, different tools have specialized in fields such as Solidworks on 3D part and assembly modeling and Catia on surface modeling. One application scenario of those tools for DT engineering, is to model individual machine components and assemble them to describe an entire machine tool structure. For example, Cai et al. [22] separated the components into moving parts (spindle, work table, moving frame) and stationary parts (machine bed, column) to enable virtualization of machine appearance and motion.

Engineering systems modeling and simulation software import CAD models and provide functionality for simulating machine tools, manufacturing processes, and collaborative robot systems. For example, Havard et al. [46] used the Delmia toolbox that includes Catia for modeling and Modelica for simulating robot motion. Furthermore, Modelica language supports multi-domain modeling, as needed for describing complex manufacturing entities [84]. In addition, the graphical programming interface in Modelica (OpenModelica Connection Editor) increases usability for non-programmers [5]. Furthermore, Malik and Brem [86] used Tecnomatix Plant Simulation for simulating the task sequence of a collaborative robot assembly station. Also, Tecnomatix Plant Simulation can import virtual representations of humans, 3D CAD models of robots, and models of the surroundings to conduct an ergonomic assessment of the workstation. An alternative engineering software specialist in simulating robot systems is ROS, an open-source tool with modules for kinematic modeling (URDF), motion planning, and control (MoveIt) [143].

Computation and machine learning tools

Following, we summarized findings on software tools for computational and machine learning tasks.

Suppose first principles modeling techniques cannot accurately predict system response or knowledge about the underlying process is unavailable. In that case, data analysis and computational learning approaches can be essential in creating DT models and services. Modules in Python programming language and machine learning platforms such as TensorFlow support the adoption of computational learning applications. For example, Matulis and Harvey [87] used TensorFlow for training a robot to perform specific tasks by learning in a simulation environment. Similarly, libraries are available for computer vision applications. For example, Moretti et al. [92] used Matlab's Image Processing, and Computer Vision Toolbox for contour detection of 3D printed layers from microscopic image files.

Furthermore, several authors used programming languages such as Matlab and Python to automate data-related tasks and to script algorithms for performing custom functionality within the DT.

Visualization software tools

We grouped software tools for visualization in DTs into web-based visualization and 3D simulation engines. Of the 12 papers that used visualization tools, 9 used 3D simulation engines, and 3 used web-based visualizations.

3D simulation engines support the development of interactive 3D applications through user interfaces, and virtual or augmented reality. They are also used during the development of the DTs in the context of creating models using machine learning or testing the system.

We found that the most frequently used simulation engine was Unity, and it was used in different manners: user interface, virtual reality, and model development. For example, Mourtzis et al. [93] created a GUI showing 3D visualizations of the system in Unity; Havard et al. [46], Zhang et al. [148] used Unity and Virtual Reality to assess the design and safety of industrial workstations by creating 3D visualizations where operators can interact with the environment; and Matulis and Harvey [87] trained a robotic arm to learn to identify and move colored objects using Unity and reinforcement learning. Furthermore, the 3D simulation engines Flexsim and Gazebo were also found to be used. For example, Lohtander et al. [78] used FlexSim and Virtual Reality to create a 3D model of a manufacturing unit; and Bansal et al. [16] used Gazebo for simulating a valid, collision-free path for a UR5 robot. Additionally, Tecnomatix Plant Simulator had been used by Malik and Brem [86] to perform experiments on human-robot collaboration tasks and visualize the sweeping area of the robotic arms. Redelinghuys et al. [111] created a customizable interface in Tecnomatix to simulate and diagnose faults by comparing a reference model with simulated behavior. The RViz module in the ROS ecosystem enables 3D visualization and simulation of robot systems and is used by [143] for visualizing a robot system by importing the robot description using URDF files.

It is clear that 3D simulation engines are useful in various stages of DTs, as they can be used for more than just visualizing DTs. As illustrated, there are many choices for 3D simulation engines that can be used with DTs. It is important to choose a simulation engine that is relevant to the specific application. The simulation engines have different capabilities; some of them, such as FlexSim, perform discrete-event simulations which is typically sufficient for visualization, while others, such as Gazebo, use physics engines that allow simulation of rigid-body dynamics and collision detection. Depending on the purpose of the DT, the developers should consider which type of simulation engine is the most suitable. For example, if the visualization is also used in modeling the dynamics of the DT, then it may be necessary to use a physics-based simulation engine.

Web-based visualization frameworks support the development of visualization applications accessible through the web. For example, Tammaro et al. [127] used the X3DOM library to create a web-based 3D visual interface; Hoebert et al. [51] implemented a cloud-based server for visualizing a digital model of the physical entity on a web browser using the JavaScript libraries BabylonJS and WebGL; and Huynh et al. [56] used the JavaScript WebGL application interface to visualize robotic arms on a webpage.

The literature shows web-based visualization has mainly been used in the deployed DT through a user interface, whilst 3D simulation engines have both been used in the development phases of the DT and also in the deployed DT. Although web-based visualization is limited to solely visualizing a system or parts of a system, it is easier for users to utilize in the end product, as they do not require installing a specific simulation engine.

Summary and discussion on digital twin deployment

Manufacturing domains and system types characterize the physical entities that DTs were deployed. Our review indicates that the most prominent domains are separation processes, advanced robotics, and additive manufacturing. Further, DTs were reported for three system types (closed, open, and hybrid system) that have their individual strengths and weaknesses. The main challenge of closed systems is that only high-level functions (such as status and execution monitoring) are accessible. Minimal access is given to low-level execution of elemental control settings (setting controller and providing control references). Thus, entering the control loop and achieving virtual-to-physical feedback was rarely achieved in the reviewed literature. Moreover, the transferal of extensive data can burden control stability and network capacity in closed systems. When sending extensive data, in the best case, internal processing is prioritized by interrupting data transferal, or in the worst case, regular operation of the CNC control is influenced [20,23]. The best DT' can hope for is fine-tuning parameters that can usually be configured for closed systems.

Open and hybrid systems typically lack industrial relevance when deploying DTs. The lack of relevance originates from the fact that most open systems were built to demonstrate DT deployment in a laboratory environment. Moreover, hybrid systems improved the capabilities to acquire data from a closed system, but the challenge of sending control commands from the virtual entity and using external sensors outside an experimental environment remains. Schemes for rating open architecture control units, as shown in [29], can help to define requirements and guide towards increasing the openness of control architectures. Furthermore, for purchasing new machine tools these evaluation schemes help to determine machines' maturity level regarding DT deployment, if adopted appropriately to the DT domain.

The twinning rate can be classified by three different methods: continuous, event-based, and time-based. The most prominent example reported was the continuous method where most publications (25) characterized the twinning rate as being real-time. However, the meaning of real-time can vary depending on the application. Therefore, we want to highlight the importance to define requirements and constraints of the DT system such as demonstrated in [32], and carefully consider the trade-offs between the twinning rate and other factors such as accuracy and computational cost before selecting a suitable twinning rate. Furthermore, we recommend that a standardized reporting format be used in future DT publications of metrics quantifying twinning rates comparable to guidelines provided in [60]. This would allow comparing the twinning performance of different DT applications.

Software tools exist for a variety of specific applications. We found three categories of software tools: engineering, computation and machine learning, and visualization. Engineering software comprises software tools for industrial automation, such as PLC programming and computer-aided software tools, typically for geometric modeling and software for modeling and simulation of engineering systems. Computation and machine learning tools include programming languages for scripting and libraries for creating data-driven models. Finally, visualization tools comprise web-based visualization tools and 3D simulation engines. There exists modeling software for creating multi-domain models, computation and machine learning frameworks to create data-driven models and automation software for establishing a connection with the PLC of the physical entity. However, most DTs relied on multiple software tools and homemade interfaces. To enable industry-ready solutions, DTs need integrated software frameworks including all modeling aspects and functionality to establish the connection between a virtual and physical entity.

Discussions and conclusions

This article provides an overview of state-of-the-art research on methods and technologies for developing and implementing manufacturing DTs at the unit level. The research interest measured by publication count in this domain has been growing since 2017 in the manufacturing-, electronic- as well as computer-engineering communities. We divided the reviewed technologies for unit level DTs into four categories (generic reference models, services, content, and deployment). Further, we summarized key information in tables with links to associated references. The tables included information such as an overview of services, modeling techniques by model type, and communication protocol stacks found in the corpus of DT literature. From a research perspective, we give an overview of open research avenues in those four categories. From a practitioner's point of view, we provide support to evaluate and select appropriate technologies for engineering a DT with real-time control requirements.

The main distinguishing factor of this work is our focus on the unit level. The motivation to conduct a systematic review focused on unit level DT emerged as unit level applications, as opposed to system or system-of-systems level applications, require control feedback within a smaller timeframe such as for motion control of robotic manipulators and process control in machining. We identified that related reviews did not provide a dedicated effort in this direction. Limitations of this review are: 1) We identified and used keywords sufficient to answer our research questions and assume that a more inclusive search, e.g., using wildcard characters, would further broaden the corpus of literature, 2) we expect parts of the contribution to quickly change in the future such as information technologies and software tools for DTs, and 3) we focused on contribution specific to DTs research and purposefully not included parallel research streams.

Summary of key contributions and research gaps

Distinguishing DTs and simulation-enabled manufacturing applications can be challenging. Kritzinger et al. [66] presents a terminology clearly separating the terms Digital model, Digital shadow, and DT from each other. However, the term DT is used inconsistently in the investigated literature and most references do not share the same definition. This lack of precision of what a DT is, leads to the current confusion and misunderstandings, as different authors use the term to refer to different concepts thus making it difficult for readers to grasp the essence of the DT concept. Further, the development of standards and best practices is hampered, as there are no agreed criteria or guidelines for what constitutes a DT. This can hinder the interoperability and compatibility of DT systems. Last, the inconsistent usage makes it challenging for researchers to evaluate and compare DTs that are based on different terminology and concepts, which can limit the ability of the field to advance and innovate as there may be duplicated work or missed opportunities for collaboration.

Generic reference models: Unit level DTs in manufacturing are constructed from four prominent reference models: 3D, 5D, hierarchical and life cycle models. They exist in a variety of manifestations and are typically described at a high conceptual level. For most generic models, it remains unclear for which use case they are applicable and how to apply them. Some papers adopted existing standards from the automation and manufacturing domain and applied them to DTs. However, a standardized generic model with a unified terminology is missing.

Services: Four primary services (monitoring, optimization, visualization, product customization) are provided by unit level DTs. The majority of DT services are related to monitoring and optimization tasks. The lack of suitable hardware and software tools deprives the industry of fully developing and implementing DT services requiring responses with high temporal frequencies. Despite the importance, model calibration services are implemented by a minority of unit level DTs. DTs without proper calibration methods provide a snapshot of the current entity state and cannot evolve with the physical entity. This lack of synchronization for some unit level DTs further fuels the discussion on misstatement and misuse of the term DT [66].

Content: Unit level DTs are developed using four types of models (geometric, physical, behavior, and rule-based), data collected from various sources, and industrial communication protocols. Creating adequate models and acquiring a sufficient data foundation are the elementary tasks when engineering DTs, and require a significant and dedicated effort.

For representing the physical entity, e.g., machine tool, process, and environment, typically geometric and physical models are used. It is very rare that advanced techniques, i.e., hybrid, behavioral, and rule-based models, are used. The focus on basic modeling techniques is primarily caused by the need for data availability and more insights in modern machine tool systems that else are a black box for the end user of the machine tool. Further, data is acquired using a variety of industrial communication protocols such as OPC-UA, MTConnect, and MQTT. To date, not all machines, e.g., legacy machines frequently found on an industrial shop floor, support those protocols. Moreover, the majority of DT implementations are lab-scale developments in contrast to real-world applications. The lab-scale nature of those DTs results in simplification compared to an industrial use case such as only occasional use of storage technologies and low availability of historical data.

Deployment: Unit level DTs are deployed to three types of physical systems (closed, open, and hybrid). The typical industrial production unit characterizes as a closed system. For closed systems, intrinsic support to collect relevant sensor data from the physical entity and to receive control commands from the virtual entity is not available. DTs may configure high-level parameters for closed systems but DT-based real-time feedback will continue to be rarely achieved for the foreseeable future. In general, it is advisable to choose appropriate sampling and twinning rates that are suitable for the specific application in order to attain the desired level of accuracy and avoid unnecessary consumption of computational resources. Application-specific software tools (engineering, computation, and machine learning and visualization) are used for DT deployment. Typically DTs relied on an application-specific composition of multiple software tools. Thus, interfaces for connecting those tools are required. However, engineering reusable interfaces is challenging because of the high variability in the composition of those tools.

Future directions

Advances in standardized generic models: The literature review suggests that advances in standardized generic models will facilitate unifying the models' terminology. A unified process for constructing a generic reference model can help to specify rules for engineering and operating DTs. Further, standardization efforts can improve interoperability between DTs. Improved interoperability of DTs can help in composing system of systems of DTs. In contrast, interoperability of elements, such as services, models, and data, within a single DT can accelerate engineering a DT by reusing elements that have proven usage history.

Model and data access: Easy access to digital copies of physical systems, e.g., during purchasing of a physical system the virtual counterpart is also supplied, can speed DT development and can free resources to focus on the development of advanced models. To enable interoperability of models and tools, and maintain the intellectual property rights of the machine tool builders, the applicability of technologies such as co-simulation and the Functional Mockup Interface Standard should be investigated [41].

Twinning rate and scope: Another, DT research field currently lacking focus is the development of methodologies, techniques, and tools for evaluating, optimizing, and selecting appropriated twinning rates and scopes such as proposed in [4,64]. Specifically, methodologies for determining the optimal twinning rate and scope for a given application should be developed. This involves considering factors such as the complexity of the physical system, the availability and quality of data, and the computational resources available. In this context, empirical studies should be conducted to evaluate how different twinning rates and scopes affect the accuracy of DTs and the computational resources required to simulate the physical system. Furthermore, evaluating the robustness and reliability of DTs with respect to different twinning rates and scopes may be required.

Integrated software frameworks: Furthermore, new and improved software tools and hardware solutions can pave the way for applying services, executing models, and conducting computations in a timely manner to serve the physical entity within the required timeframe. Particularly, integrated software frameworks can enable industrial practitioners to quickly demonstrate value and iteratively improve DTs solutions without requiring major development efforts of custom interfaces.

In conclusion, despite the rapid increase of research on unit level DTs most papers focus on specific parts of the DT as opposed to being holistic, and only a few present industrial-relevant applications. Further, there exists a need for a clear definition of DT in the industry and improved semantic interoperability between a wide variety of domains. At last, we want to highlight the need for research on establishing the virtual-to-physical connection and on methods for controlling the physical entity in a timely manner by its virtual counterpart for successfully engineering DTs at the unit-level.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] 21838-2:2021, I., 2021.Information technology — Top-level ontologies. Technical Report. International Organizationfor Standardization.
[2] Abraham, J.C., Cruz, G., Cubela, S., Lajous, T., Rowshankish, K., Tiwari, S., Zemmel, R., 2020.lDigital twins: From one twin to the enterprise metaverse. McKinsey Digital. McKinsey.
[3] Agnusdei, G.P., Elia, V., Gnoni, M.G., 2021.Is digital twin technology supporting safety management? a bibliometric and systematic review. Applied Sciences (Switzerland) 11.10.3390/app11062767.
[4] Agrawal, A., Fischer, M., Singh, V., 2022, Digital Twin: From Concept to Practice. Journal of Management in Engineering, 38:06022001.
[5] Aivaliotis, P., Georgoulias, K., Chryssolouris, G., 2019, The Use of Digital Twin for Predictive Maintenance in Manufacturing. International Journal of Computer Integrated Manufacturing, 32:1067–1080. https://doi.org/10.1080/0951192X.2019.1686173.
[6] Alexopoulos, K., Nikolakis, N., Chryssolouris, G., 2020, Digital Twin-driven Supervised Machine Learning for the Development of Artificial Intelligence Applications in Manufacturing. International Journal of Computer Integrated Manufacturing, 33:429–439. https://doi.org/10.1080/0951192X.2020.1747642.
[7] Ameri, F..Msdl. Available at 〈https://infoneer.wp.txstate.edu/ontology-download/msdl-ontology/〉(2022 /05/30).
[8] de Andrade, M.A.N., Lepikson, H.A., Machado, C.A.T., 2021.A New Framework and Methodology for Digital Twin Development.2021 14th IEEE International Conference on Industry Applications, INDUSCON 2021 - Proceedings 14, 134–138.10.1109/INDUSCON51756.2021.9529701.
[9] Angrish, A., Starly, B., Lee, Y.S., Cohen, P.H., 2017, A Flexible Data Schema and System Architecture for the Virtualization of Manufacturing Machines (VMM). Journal of Manufacturing Systems, 45:236–247. https://doi.org/10.1016/j.jmsy.2017.10.003.
[10] Arkouli, Z., Aivaliotis, P., Makris, S., 2020, Towards Accurate Robot Modelling of Flexible Robotic Manipulators. Procedia CIRP. Elsevier B.V.,: 497–501. https://doi.org/10.1016/j.procir.2020.07.009.
[11] Atalay, M., Murat, U., Oksuz, B., Parlaktuna, A.M., Pisirir, E., Testik, M.C., 2022, Digital Twins in Manufacturing: Systematic Literature Review for Physical–digital Layer Categorization and Future Research Directions. International Journal of Computer Integrated Manufacturing, 1–27.
[12] Ayani, M., Ganebäck, M., Ng, A.H., 2018, Digital Twin: Applying Emulation for Machine Reconditioning. Procedia CIRP. Elsevier B.V.: 243–248. https://doi.org/10.1016/j.procir.2018.03.139.
[13] Balderas, D., Ortiz, A., Méndez, E., Ponce, P., Molina, A., 2021, Empowering Digital Twin for Industry 4.0 Using Metaheuristic Optimization Algorithms: Case Study PCB Drilling Optimization. International Journal of Advanced Manufacturing Technology, 113:1295–1306. https://doi.org/10.1007/s00170-021-06649-8.
[14] Balta, E.C., Tilbury, D.M., Barton, K., 2019, A Digital Twin Framework for Performance Monitoring and Anomaly Detection in Fused Deposition Modeling. IEEE International Conference on Automation Science and Engineering. IEEE Computer Society: 823–829. https://doi.org/10.1109/COASE.2019.8843166.
[15] Bamunuarachchi, D., Banerjee, A., Jayaraman, P.P., Georgakopoulos, D., 2020, Cyber Twins Supporting Industry 4.0 Application Development. ACM International Conference Proceeding Series, 64–73. https://doi.org/10.1145/3428690.3429177.
[16] Bansal, R., Khanesar, M.A., Branson, D., 2019. Ant Colony Optimization Algorithm for Industrial Robot Programming in a Digital Twin, In: ICAC 2019 - 2019 25th IEEE International Conference on Automation and Computing, Institute of Electrical and Electronics Engineers Inc.10.23919/IConAC.2019.8895095.
[17] Baskaran, S., Niaki, F.A., Tomaszewski, M., Gill, J.S., Chen, Y., Jia, Y., Mears, L., Krovi, V., 2019, Digital Human And Robot Simulation In Automotive Assembly Using Siemens Process Simulate: A Feasibility Study. Procedia Manufacturing. Elsevier B.V.: 986–994. https://doi.org/10.1016/j.promfg.2019.06.097.
[18] Bazaz, S.M., Lohtander, M., Varis, J., 2020, The Prediction Method of Tool Life on Small Lot Turning Process - Development of Digital Twin for Production. Procedia Manufacturing, 51:288–295. https://doi.org/10.1016/j.promfg.2020.10.041.
[19] Bibow, P., Dalibor, M., Hopmann, C., Mainz, B., Rumpe, B., Schmalzing, D., Schmitz, M., Wortmann, A., 2020.Model-Driven Development of a Digital Twin for Injection Molding.Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 12127 LNCS, 85–100.10.1007/978-3-030-49435-3_6.
[20] Caesar, B., Hänel, A., Wenkler, E., Corinth, C., Ihlenfeldt, S., Fay, A., 2020. Information Model of a Digital Process Twin for Machining Processes, in: IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, Institute of Electrical and Electronics Engineers Inc. 1765–1772.10.1109/ETFA46521.2020.9212085.
[21] Cahyati, S., Syaifudin, Achdianto, 2019, A Prototyping of Additive Manufacturing Cell in Cyber Physical System for Maintenance 4.0 Preparation. International Journal of Advanced Science and Technology, 29:575–584〈https://www.scopus.com/inward/record.uri?eid=2-s2.0-85083524743&partnerID=40&md5=2c906dd249864ef01f795bb0fcbf95d6〉.
[22] Cai, Y., Starly, B., Cohen, P., Lee, Y.S., 2017, Sensor Data and Information Fusion to Construct Digital-twins Virtual Machine Tools for Cyber-physical Manufacturing. Procedia Manufacturing, 10:1031–1042. https://doi.org/10.1016/j.promfg.2017.07.094.
[23] Cao, X., Zhao, G., Xiao, W., 2020, Digital Twin-oriented Real-time Cutting Simulation for Intelligent Computer Numerical Control Machining. in: Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture. https://doi.org/10.1177/0954405420937869.
[24] Cardin, O., Castagna, P., Couedel, D., Plot, C., Launay, J., Allanic, N., Madec, Y., Jegouzo, S., 2020, Energy-aware Resources in Digital Twin: the Case of Injection Moulding Machines. Studies in Computational Intelligence, 853:183–194. https://doi.org/10.1007/978-3-030-27477-1_14.
[25] Cattaneo, L., MacChi, M., 2019, A Digital Twin Proof of Concept to Support Machine Prognostics with Low Availability of Run-To-Failure Data. IFAC-PapersOnLine. Elsevier B.V.: 37–42. https://doi.org/10.1016/j.ifacol.2019.10.016.
[26] Chen, G., Zhu, J., Zhao, Y., Hao, Y., Yang, C., Shi, Q., 2021, Digital Twin Modeling for Temperature Field During Friction Stir Welding. Journal of Manufacturing Processes, 64:898–906. https://doi.org/10.1016/j.jmapro.2021.01.042.
[27] Chen, X., Yan, N., Wang, C., Ding, P., 2020.Study on straightening quality control for slender rod based on digital twin 1633.10.1088/1742-6596/1633/1/012160.
[28] Chhetri, S.R., Faezi, S., Canedo, A., Faruque, M.A.A., 2019.QUILT: Quality inference from living digital twins in IoT-enabled manufacturing systems, In: IoTDI 2019 - Proceedings of the 2019 Internet of Things Design and Implementation, Association for Computing Machinery, Inc.237–248.10.1145/3302505.3310085.
[29] Chi, Y., 2005, An Evaluation Space For Open Architecture Controllers. International Journal of Advanced Manufacturing Technology, 26:351–358. https://doi.org/10.1007/s00170-004-2111-x.
[30] Ciano, M.P., Pozzi, R., Rossi, T., Strozzi, F., 2020, Digital Twin-enabled Smart Industrial Systems: a Bibliometric Review. International Journal of Computer Integrated Manufacturing. https://doi.org/10.1080/0951192X.2020.1852600.
[31] Cimino, C., Negri, E., Fumagalli, L., 2019, Review of Digital Twin Applications in Manufacturing. Computers in Industry, 113. https://doi.org/10.1016/j.compind.2019.103130.
[32] Dobaj, J., Riel, A., Macher, G., Egretzberger, M., 2022. A Method for Deriving Technical Requirements of Digital Twins as Industrial Product-service System Enablers, In: Systems, Software and Services Process Improvement: 29th European Conference, EuroSPI 2022, Salzburg, Austria, August 31–September 2, 2022, Proceedings, Springer.378–392.
[33] Eisenbarth, D., Soffel, F., Wegener, K., 2020, Geometry-Based Process Adaption to Fabricate Parts with Varying Wall Thickness by Direct Metal Deposition. Lecture Notes in Mechanical Engineering, 125–130. https://doi.org/10.1007/978-3-030-29041-2_16.
[34] Errandonea, I., Beltrán, S., Arrizabalaga, S., 2020, Digital Twin For Maintenance: a Literature Review. Computers in Industry, 123. https://doi.org/10.1016/j.compind.2020.103316.
[35] Ertveldt, J., Guillaume, P., Helsen, J., 2020, MiCLAD as a Platform for Real-time Monitoring and Machine Learning in Laser Metal Deposition. Procedia CIRP. Elsevier B.V.,: 456–461. https://doi.org/10.1016/j.procir.2020.09.164.
[36] Fernández, I.A., Aguirre Ortuzar, A., Andrés, J.U., Eciolaza Echeverría, L., 2020. ADAPT: An Automatic Diagnosis of Activity and Processes in Automation Environments, In: IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, Institute of Electrical and Electronics Engineers Inc., 945–951.10.1109/ETFA46521.2020.9211996.
[37] Gaikwad, A., Yavari, R., Montazeri, M., Cole, K., Bian, L., Rao, P., 2020, Toward the Digital Twin of Additive Manufacturing: Integrating Thermal Simulations, Sensing, And Analytics to Detect Process Faults. IISE Transactions, 52:1204–1217. https://doi.org/10.1080/24725854.2019.1701753.

[38] RaúlGarcía-Castro, R.A., Lieberman, J., Stadler, C. Semantic sensor network ontology. Available at ⟨https://www.w3.org/TR/vocab-ssn/⟩(2022 /05/30).
[39] Garlan, D., Shaw, M., 1994. An Introduction to Software Architecture. Technical Report CMU/SEI-94-TR-021. Software Engineering Institute, Carnegie Mellon University. Pittsburgh, PA.⟨http://resources.sei.cmu.edu/library/asset-view.cfm?AssetID=12235⟩.
[40] German Institute for Standardisation Registered Association, 2033.DIN 8580:2003–09: Manufacturing processes - Terms and definitions, division. German Institute for Standardisation Registered Association.⟨https://tinyurl.com/din8580⟩.
[41] Gomes, C., Meyers, B., Denil, J., Thule, C., Lausdahl, K., Vangheluwe, H., De Meulenaere, P., 2019, Semantic Adaptation for Fmi Co-simulation with Hierarchical Simulators. Simulation, 95:241–269.
[42] Grieves, M., 2015, Digital Twin: Manufacturing Excellence Through Virtual Factory Replication. White Paper.
[43] H2020 CSA project, 2020.Ontology-driven data documentation for industry commons.⟨https://ontocommons.eu/⟩.
[44] Hänel, A., Schnellhardt, T., Wenkler, E., Nestler, A., Brosius, A., Corinth, C., Fay, A., Ihlenfeldt, S., 2020, The Development of A Digital Twin for Machining Processes for the Application in Aerospace Industry. Procedia CIRP. Elsevier B.V.: 1399–1404. https://doi.org/10.1016/j.procir.2020.04.017.
[45] Hartmann, D., Herz, M., Wever, U., 2018, Model Order Reduction a Key Technology for Digital Twins. Reduced-Order Modeling (ROM) for Simulation and Optimization: Powerful Algorithms as Key Enablers for Scientific Computing, 167–179.
[46] Havard, V., Jeanne, B., Lacomblez, M., Baudry, D., 2019, Digital Twin and Virtual Reality: a Co-simulation Environment for Design and Assessment of Industrial Workstations. Production and Manufacturing Research, 7:472–489. https://doi.org/10.1080/21693277.2019.1660283.
[47] He, B., Bai, K.J., 2021, Digital Twin-based Sustainable Intelligent Manufacturing: a Review. Advances in Manufacturing, 9:1–21.
[48] Hibbeler, R.C., 2009, Engineering Mechanics: Dynamics. Pearson Education, USA.
[49] Hinchy, E.P., Carcagno, C., O'Dowd, N.P., McCarthy, C.T., 2020, Using Finite Element Analysis to Develop a Digital Twin of a Manufacturing Bending Operation. Procedia CIRP. Elsevier B.V.: 568–574. https://doi.org/10.1016/j.procir.2020.03.031.
[50] Hinchy, E.P., O'Dowd, N.P., McCarthy, C.T., 2019, Using Open-source Microcontrollers to Enable Digital Twin Communication for Smart Manufacturing. Procedia Manufacturing. Elsevier B.V.: 1213–1219. https://doi.org/10.1016/j.promfg.2020.01.212.
[51] Hoebert, T., Lepuschitz, W., List, E., Merdan, M., 2019.Cloud-Based Digital Twin for Industrial Robotics. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 11710 LNAI, 105–116.10.1007/978-3-030-27878-6_9.
[52] Horváth, G., Erdos, G., 2017, Gesture Control of Cyber Physical Systems. Procedia CIRP. Elsevier B.V.: 184–188. https://doi.org/10.1016/j.procir.2017.03.312.
[53] Hu, L., Nguyen, N.T., Tao, W., Leu, M.C., Liu, X.F., Shahriar, M.R., AlSunny, S.M., 2018, Modeling of Cloud-Based Digital Twins for Smart Manufacturing with MT Connect. Procedia Manufacturing. Elsevier B.V.: 1193–1203. https://doi.org/10.1016/j.promfg.2018.07.155.
[54] Huang, S., Wang, G., Yan, Y., 2020, Building Blocks for Digital Twin of Reconfigurable Machine Tools from Design Perspective. International Journal of Production Research. https://doi.org/10.1080/00207543.2020.1847340.
[55] Hürkamp, A., Gellrich, S., Ossowski, T., Beuscher, J., Thiede, S., Herrmann, C., Dröder, K., 2020, Combining Simulation and Machine Learning as Digital Twin for the Manufacturing of Overmolded Thermoplastic Composites. Journal of Manufacturing and Materials Processing, 4. https://doi.org/10.3390/JMMP4030092.
[56] Huynh, B.H., Akhtar, H., Sett, M.K., 2019. A Universal Methodology to Create Digital Twins for Serial and Parallel Manipulators, In: Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics, Institute of Electrical and Electronics Engineers Inc., 3104–3109.10.1109/SMC.2019.8914195.
[57] Industrial Ontologies Foundry. Industrial ontologies. Available at ⟨https://www.industrialontologies.org/⟩ (2022 /05/30).
[58] ISO 23247:2021, 2021.Automation systems and integration - Digital Twin framework for manufacturing. Technical Report. International Organization for Standardization.
[59] Janda, P., Hajicek, Z., Bernardin, P., 2019.Implementation of the Digital Twin Methodology, in: Annals of DAAAM and Proceedings of the International DAAAM Symposium, Danube Adria Association for Automation and Manufacturing, DAAAM.533–538.10.2507/30th.daaam.proceedings.072.
[60] Jedlitschka, A., Ciolkowski, M., Pfahl, D., 2008, Reporting Experiments in Software Engineering. Guide to Advanced Empirical Software Engineering, 201–228.
[61] Jones, D., Snider, C., Nassehi, A., Yon, J., Hicks, B., 2020, Characterising the Digital Twin: A Systematic Literature Review. CIRP Journal of Manufacturing Science and Technology, 29:36–52. https://doi.org/10.1016/j.cirpj.2020.02.002.
[62] Khanesar, M.A., Bansal, R., Martínez-Arellano, G., Branson, D.T., 2020, XOR Binary Gravitational Search Algorithm with Repository: Industry 4.0 applications. Applied Sciences (Switzerland), 10. https://doi.org/10.3390/APP10186451.
[63] Kim, J., 2017, A Review of Cyber-physical System Research Relevant to the Emerging it Trends: Industry 4.0, IOT, Big Data, And Cloud Computing. Journal of Industrial Integration and Management, 02:1750011. https://doi.org/10.1142/S2424862217500117.
[64] Kober, C., Adomat, V., Ahanpanjeh, M., Fette, M., Wulfsberg, J.P., 2022, Digital twin fidelity requirements model for manufacturing. Proceedings of the Conference on Production Systems and Logistics: CPSL 2022. publish-Ing.,, Hannover: 595–611.
[65] Krima, S., Barbau, R., Fiorentini, X., Rachuri, S., Sriram, R., 2009. Ontostep: Owl-dl Ontology for Step.⟨https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=901544⟩.
[66] Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., 2018, Digital Twin in Manufacturing: A Categorical Literature Review and Classification. IFAC-PapersOnLine, 51:1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474.
[67] Kubota, T., Liu, C., Mubarok, K., Xu, X., 2018.A Cyber-physical Machine Tool Framework Based on STEP-NC, In: Proceedings of International Conference on Computers and Industrial Engineering, CIE, Curran Associates Inc.⟨https://www.scopus.com/inward/record.uri?eid=2-s2.0-85061300916&partnerID=40&md5=a8231a05896b5fe286f2a7d9d05d20f3⟩.
[68] Kutin, A.A., Bushuev, V.V., Molodtsov, V.V., 2019. Digital Twins of Mechatronic Machine Tools for Modern Manufacturing, In: IOP Conference Series: Materials Science and Engineering, Institute of Physics Publishing.10.1088/1757-899X/568/1/012070.
[69] Kutscher, V., Anokhin, O., Anderl, R., 2020, Enhancing Digital Twin Performance Through Simulation of Computerized Numerical Control Firmware. Procedia Manufacturing. Elsevier B.V.,: 69–74. https://doi.org/10.1016/j.promfg.2020.06.013.
[70] Kutscher, V., Ruland, S., Müller, P., Wasser, N., Lochau, M., Anderl, R., Schürr, A., Mezini, M., Hähnle, R., 2020, Towards a Circular Economy of Industrial Software. Procedia CIRP. Elsevier B.V.,: 37–42. https://doi.org/10.1016/j.procir.2020.01.133.
[71] Laboratory, C.S., 1993.Integration Definition for Information Modeling.IDEF1X.
[72] Lawrence, M., Hendershot, R., Guha, A., Dines, M., 2020, Digital Twin Methodology Improves Performance and Yield in an Aluminum Tilt Rotary Furnace. Light Metal Age, 78:54–56⟨https://www.scopus.com/inward/record.uri?eid=2-s2.0-85096116093&partnerID=40&md5=2c4a346f226d4d8bc28575d208151 21f⟩.
[73] Lermer, M., Reich, C., 2019.Creation of Digital Twins by Combining Fuzzy Rules with Artificial Neural Networks, In: IECON Proceedings (Industrial Electronics Conference), IEEE Computer Society.5849–5854.10.1109/IECON.2019.8926914.
[74] Liu, J., Du, X., Zhou, H., Liu, X., ei Li, L., Feng, F., 2019, A Digital Twin-based Approach for Dynamic Clamping and Positioning of the Flexible Tooling System. Procedia CIRP, 80:746–749. https://doi.org/10.1016/j.procir.2019.01.063.
[75] Liu, J., Zhou, H., Liu, X., Tian, G., Wu, M., Cao, L., Wang, W., 2019, Dynamic Evaluation Method of Machining Process Planning Based on Digital Twin. IEEE Access, 7:19312–19323. https://doi.org/10.1109/ACCESS.2019.2893309.
[76] Liu, M., Fang, S., Dong, H., Xu, C., 2020, Review of Digital Twin about Concepts, Technologies, and Industrial Applications. Journal of Manufacturing Systems.
[77] Liu, S., Bao, J., Lu, Y., Li, J., Lu, S., Sun, X., 2021, Digital Twin Modeling Method Based on Biomimicry for Machining Aerospace Components. Journal of Manufacturing Systems, 58:180–195. https://doi.org/10.1016/j.jmsy.2020.04.014.
[78] Lohtander, M., Ahonen, N., Lanz, M., Ratava, J., Kaakkunen, J., 2018, Micro Manufacturing Unit and the Corresponding 3D-Model for the Digital Twin. Procedia Manufacturing, 25:55–61. https://doi.org/10.1016/j.promfg.2018.06.057.
[79] López, C.E.B., 2021, Real-time Event-based Platform for The Development of Digital Twin Applications. The International Journal of Advanced Manufacturing Technology, 116:835–845.
[80] López-Estrada, L., Fajardo-Pruna, M., Gualoto-Condor, S., Ríos, J., Vizán, A., 2019, Creation of a Micro Cutting Machine Tool Digital-twin Using a Cloud-based Model-based PLM Platform: First Results. Procedia Manufacturing, 41:137–144. https://doi.org/10.1016/j.promfg.2019.07.039.
[81] Lu, Y., Liu, C., Kevin, I., Wang, K., Huang, H., Xu, X., 2020, Digital Twin-driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues. Robotics and Computer-Integrated Manufacturing, 61:101837.
[82] Lu, Y., Xu, X., 2018, Resource Virtualization: A Core Technology for Developing Cyber-physical Production Systems. Journal of Manufacturing Systems, 47:128–140. https://doi.org/10.1016/j.jmsy.2018.05.003.
[83] Luo, W., Hu, T., Ye, Y., Zhang, C., Wei, Y., 2020, A Hybrid Predictive Maintenance Approach for CNC Machine Tool Driven by Digital Twin. Robotics and Computer-Integrated Manufacturing, 65. https://doi.org/10.1016/j.rcim.2020.101974.
[84] Luo, W., Hu, T., Zhang, C., Wei, Y., 2019, Digital Twin for CNC Machine Tool: Modeling and Using Strategy. Journal of Ambient Intelligence and Humanized Computing, 10:1129–1140. https://doi.org/10.1007/s12652-018-0946-5.
[85] Malik, A.A., Bilberg, A., 2018, Digital Twins of Human Robot Collaboration in a Production Setting. Procedia Manufacturing. Elsevier B.V.: 278–285. https://doi.org/10.1016/j.promfg.2018.10.047.
[86] Malik, A.A., Brem, A., 2021, Digital Twins for Collaborative Robots: A Case Study in Human-robot Interaction. Robotics and Computer-Integrated Manufacturing, 68. https://doi.org/10.1016/j.rcim.2020.102092.
[87] Matulis, M., Harvey, C., 2021, A Robot Arm Digital Twin Utilising Reinforcement Learning. Computers and Graphics (Pergamon), 95:106–114. https://doi.org/10.1016/j.cag.2021.01.011.

[88] Melesse, T.Y., DiPasquale, V., Riemma, S., 2020, Digital Twin Models In Industrial Operations: A Systematic Literature Review. Procedia Manufacturing, 42:267–272. https://doi.org/10.1016/j.promfg.2020.02.084.
[89] Miao, Q., Liu, L., Chen, C., Wan, X., Xu, T., 2021, Research on Operation Status Prediction of Production Equipment Based on Digital Twins and Multidimensional Time Series. Lecture Notes in Electrical Engineering, 737:246–254. https://doi.org/10.1007/978-981-33-6318-2_31.
[90] Moon, I., Hong, J.H., 2013. Theoretic interplay between abstraction, resolution, and fidelity in model information, In: 2013 Winter Simulations Conference (WSC), 1283–1291.10.1109/WSC.2013.6721515.
[91] Moreno, A., Velez, G., Ardanza, A., Barandiaran, I., de Infante, Á.R., Chopitea, R., 2017, Virtualisation Process of a Sheet Metal Punching Machine within the Industry 4.0 vision. International Journal on Interactive Design and Manufacturing, 11:365–373. https://doi.org/10.1007/s12008-016-0319-2.
[92] Moretti, M., Rossi, A., Senin, N., 2021, In-process Monitoring of Part Geometry in Fused Filament Fabrication Using Computer Vision and Digital Twins. Additive Manufacturing, 37. https://doi.org/10.1016/j.addma.2020.101609.
[93] Mourtzis, D., Angelopoulos, J., Panopoulos, N., 2021, Equipment Design Optimization Based on Digital Twin under the Framework of Zero-Defect Manufacturing. Procedia Computer Science. Elsevier B.V.: 525–533. https://doi.org/10.1016/j.procs.2021.01.271.
[94] Negri, E., Fumagalli, L., Macchi, M., 2017, A Review of the Roles Of Digital Twin in CPS-based Production Systems. Procedia Manufacturing, 11:939–948. https://doi.org/10.1016/j.promfg.2017.07.198.
[95] Odada, C.A., Byiringiro, J.B., Mwema, F.M., 2021.Development of Data-driven Digital Twin for Real-time Monitoring of Fdm 3D Printer.
[96] Orive, D., Iriondo, N., Burgos, A., Saráchaga, I., Álvarez, M.L., Marcos, M., 2019. Fault injection in Digital Twin as a Means To Test The Response to Process Faults at Virtual Commissioning, In: IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, Institute of Electrical and Electronics Engineers Inc., 1230–1234.10.1109/ETFA.2019.8869334.
[97] Papacharalampopoulos, A., Stavropoulos, P., Petrides, D., 2020, Towards a Digital Twin for Manufacturing Processes: Applicability on Laser Welding. Procedia CIRP. Elsevier B.V.,: 110–115. https://doi.org/10.1016/j.procir.2020.05.020.
[98] Park, H., Easwaran, A., Andalam, S., 2019. TTiLA: Twin-in-the-loop Architecture for Cyber-physical Production Systems, In: Proceedings - 2019 IEEE International Conference on Computer Design, ICCD 2019, Institute of Electrical and Electronics Engineers Inc., 82–90.10.1109/ICCD46524.2019.00019, arXiv:2003.09370.
[99] Parrott, A., Umbenhauer, B., Warshaw, L., 2020, Digital Twins: Bridging the Physical and Digital. Deloitte Insights. Deloitte.
[100] Parrott, A., Warshaw, L., 2017.Industry 4.0 and the Digital Twin: Manufacturing Meets its Match. A Deloitte Series on Industry 4.0, Digital Manufacturing Enterprises, and Digital Supply Networks. Deloitte.
[101] Pereverzev, P.P., Akintseva, A.V., Alsigar, M.K., 2020.Designing of Optimal Grinding Cycles, Sustainable to Unstable Mechanical Processing on the Basis of Synthesis of Digital Double Technology, and Dynamic Programming Method. Lecture Notes in Mechanical Engineering, 225–232.10.1007/978–3-030–22063-1_25.
[102] Polini, W., Corrado, A., 2020, Digital Twin of Composite Assembly Manufacturing Process. International Journal of Production Research, 58:5238–5252. https://doi.org/10.1080/00207543.2020.1714091.
[103] Polini, W., Corrado, A., 2021, Digital Twin of Stone Sawing Processes. International Journal of Advanced Manufacturing Technology, 112:121–131. https://doi.org/10.1007/s00170-020-06384-6.
[104] Pombo, I., Godino, L., Sánchez, J.A., Lizarralde, R., 2020, Expectations and Limitations of Cyber-physical Systems (CPS) for Advanced Manufacturing: A View From the Grinding Industry. Future Internet, 12. https://doi.org/10.3390/FI12090159.
[105] Qi, B., Park, H., 2020, Data-driven Digital Twin Model for Predicting Grinding Force. IOP Conference Series: Materials Science and Engineering IOP Publishing. https://doi.org/10.1088/1757-899X/916/1/012092.
[106] Qi, Q., Tao, F., 2018, Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. IEEE Access, 6:3585–3593. https://doi.org/10.1109/ACCESS.2018.2793265⟨https://ieeexplore.ieee.org/document/8258937⟩.
[107] Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., Wang, L., Nee, A.Y.C., 2019, Enabling Technologies and Tools for Digital Twin. Journal of Manufacturing Systems. https://doi.org/10.1016/j.jmsy.2019.10.001.
[108] Qiao, Q., Wang, J., Ye, L., Gao, R.X., 2019, Digital Twin for Machining Tool Condition Prediction. Procedia CIRP Elsevier B.V.: 1388–1393. https://doi.org/10.1016/j.procir.2019.04.049.
[109] Rasheed, A., San, O., Kvamsdal, T., 2020, Digital Twin: Values, Challenges and Enablers from a Modeling Perspective. IEEE Access, 8:21980–22012. https://doi.org/10.1109/ACCESS.2020.2970143⟨https://ieeexplore.ieee.org/document/8972429⟩.
[110] Rauch, L., Pietrzyk, M., 2019, Digital Twins as a Modern Approach to Design of Industrial Processes. Journal of Machine Engineering, 19:86–97. https://doi.org/10.5604/01.3001.0013.0456.
[111] Redelinghuys, A.J., Basson, A.H., Kruger, K., 2020, A Six-layer Architecture for the Digital Twin: a Manufacturing Case Study Implementation. Journal of Intelligent Manufacturing, 31:1383–1402. https://doi.org/10.1007/s10845-019-01516-6.
[112] Reisch, R., Hauser, T., Kamps, T., Knoll, A., 2020, Robot Based Wire Arc Additive Manufacturing System with Context-sensitive Multivariate Monitoring Framework. Procedia Manufacturing. Elsevier B.V.: 732–739. https://doi.org/10.1016/j.promfg.2020.10.103.
[113] Rosen, R., Wichert, G.V., Lo, G., Bettenhausen, K.D., 2015. About the Importance of Autonomy and Digital Twins for the Future of Manufacturing, 567–572.10.1016/j.ifacol.2015.06.141.
[114] Roy, R.B., Mishra, D., Pal, S.K., Chakravarty, T., Panda, S., Chandra, M.G., Pal, A., Misra, P., Chakravarty, D., Misra, S., 2020, Digital Twin: Current Scenario and a Case Study On A Manufacturing Process. International Journal of Advanced Manufacturing Technology, 107:3691–3714. https://doi.org/10.1007/s00170-020-05306-w.
[115] Scheffel, R.M., Fröhlich, A.A., Silvestri, M., 2021, Automated Fault Detection for Additive Manufacturing Using Vibration Sensors. International Journal of Computer Integrated Manufacturing. https://doi.org/10.1080/0951192X.2021.1901316.
[116] Schleich, B., Anwer, N., Mathieu, L., Wartzack, S., 2017, Shaping the Digital Twin for Design and Production Engineering. CIRP Annals - Manufacturing Technology, 66:141–144. https://doi.org/10.1016/j.cirp.2017.04.040.
[117] Schmidt, J., Grandi, F., Peruzzini, M., Raffaeli, R., Pellicciari, M., 2020, Novel Robotic Cell Architecture for Zero Defect Intelligent Deburring. Procedia Manufacturing. Elsevier B.V.,: 140–147. https://doi.org/10.1016/j.promfg.2020.10.021.
[118] Shahriar, M.R., Sunny, S.M.A., Liu, X., Leu, M.C., Hu, L., Nguyen, N.T., 2018. MTComm Based Virtualization and Integration of Physical Machine Operations with Digital-twins in Cyber-physical Manufacturing Cloud, In: Proceedings - CSCloud/EdgeCom 2018, Institute of Electrical and Electronics Engineers Inc. 46–51.10.1109/CSCloud/EdgeCom.2018.00018.
[119] Shatagin, D., Kuz'Mishina, A., Kolchin, P., 2020. Digital Equipment Twin as the Basis for the Consumer in Digital Production, In: IOP Conference Series: Materials Science and Engineering, Institute of Physics Publishing.10.1088/1757–899X/709/3/033081.
[120] Singh, M., Fuenmayor, E., Hinchy, E.P., Qiao, Y., Murray, N., Devine, D., 2021, Digital Twin: Origin to Future. Applied System Innovation, 4:36. https://doi.org/10.3390/ASI4020036⟨https://www.mdpi.com/2571-5577/4/2/36⟩.
[121] Sjarov, M., Lechler, T., Fuchs, J., Brossog, M., Selmaier, A., Faltus, F., Donhauser, T., Franke, J., 2020. The Digital Twin Concept in Industry–a Review and Systematization, In: 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), IEEE.1789–1796.⟨https://ieeexplore.ieee.org/document/9212089⟩, 10.1109/ETFA46521.2020.9212089.
[122] Snyder, H., 2019, Literature Review as a Research methodology: An Overview and guidelines, 104:333–339. https://doi.org/10.1016/j.jbusres.2019.07.039⟨https://www.sciencedirect.com/science/article/pii/S0148296319304564⟩.
[123] Söderberg, R., Wärmefjord, K., Carlson, J.S., Lindkvist, L., 2017, Toward a Digital Twin for Real-time Geometry Assurance in Individualized Production. CIRP Annals - Manufacturing Technology, 66:137–140. https://doi.org/10.1016/j.cirp.2017.04.038.
[124] Sonkoly, B., Nagy, B.G., Doka, J., Pelle, I., Szabo, G., Racz, S., Czentye, J., Toka, L., 2019. Cloud-Powered Digital Twins: Is It Reality?, In: Proceeding of the 2019 IEEE 8th International Conference on Cloud Networking, CloudNet 2019, Institute of Electrical and Electronics Engineers Inc. 10.1109/CloudNet47604.2019.9064112.
[125] Stachowiak, H., 1973, General Modeling Theory. Springer,.
[126] Stavropoulos, P., Papacharalampopoulos, A., Athanasopoulou, L., 2020, A Molecular Dynamics Based Digital Twin for Ultrafast Laser Material Removal Processes. International Journal of Advanced Manufacturing Technology, 108:413–426. https://doi.org/10.1007/s00170-020-05387-7.
[127] Tammaro, A., Segura, A., Moreno, A., Sánchez, J.R., 2017, Extending Industrial Digital Twins with Optical Object Tracking. Eurographics Symposium on Geometry Processing, 36:23–26. https://doi.org/10.2312/ceig.20171204.
[128] Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F., 2018, Digital Twin-driven Product Design, Manufacturing and Service with Big Data. International Journal of Advanced Manufacturing Technology, 94:3563–3576. https://doi.org/10.1007/s00170-017-0233-1.
[129] Tao, F., Qi, Q., Wang, L., Nee, A.Y.C., 2019, Digital Twins and Cyber-physical Systems Toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. Engineering, 5:653–661. https://doi.org/10.1016/j.eng.2019.01.014.
[130] Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S.C.Y., Nee, A.Y.C., 2019, Digital Twin-driven Product Design Framework. International Journal of Production Research, 57:3935–3953. https://doi.org/10.1080/00207543.2018.1443229.
[131] Tao, F., Zhang, H., Liu, A., Nee, A.Y.C., 2019, Digital Twin in Industry: State-of-the-art. IEEE Transactions on Industrial Informatics, 15:2405–2415. https://doi.org/10.1109/TII.2018.2873186.
[132] Tao, F., Zhang, M., 2017, Digital Twin Shop-floor: a New Shop-floor Paradigm Towards Smart Manufacturing. IEEE Access, 5:20418–20427. https://doi.org/10.1109/ACCESS.2017.2756069⟨https://ieeexplore.ieee.org/document/8049520⟩.
[133] Tao, F., Zhang, M., Liu, Y., Nee, A., 2018, Digital Twin Driven Prognostics and Health Management for Complex Equipment. CIRP Annals, 67:169–172. https://doi.org/10.1016/j.cirp.2018.04.055⟨https://www.sciencedirect.com/science/article/pii/S0007850618300799⟩.
[134] Tong, X., Liu, Q., Pi, S., Xiao, Y., 2020, Real-time Machining Data Application and Service Based on IMT Digital Twin. Journal of Intelligent Manufacturing, 31:1113–1132. https://doi.org/10.1007/s10845-019-01500-0.
[135] Uhlemann, T., Lehmann, C., Steinhilper, R., 2017, The Digital Twin: Realizing the Cyber-physical Production System for Industry 4.0. Procedia CIRP, 61:335–340. https://doi.org/10.1016/j.procir.2016.11.152⟨https://www.sciencedirect.com/science/article/pii/S2212827116313129⟩.

[136] VatankhahBarenji, A., Liu, X., Guo, H., Li, Z., 2020, A Digital Twin-driven Approach Towards Smart Manufacturing: Reduced Energy Consumption For a Robotic Cellular. International Journal of Computer Integrated Manufacturing. https://doi.org/10.1080/0951192X.2020.1775297.
[137] Wang, B., Hu, S.J., Sun, L., Freiheit, T., 2020, Intelligent Welding System Technologies: State-of-the-art Review and Perspectives. Journal of Manufacturing Systems, 56:373–391. https://doi.org/10.1016/j.jmsy.2020.06.020⟨https://www.researchgate.net/publication/342535030_Intelligent_Welding_System_Technologies_State-of-the-Art_Review_and_Perspectives⟩.
[138] Wang, K.J., Lee, Y.H., Angelica, S., 2020, Digital Twin Design for Real-time Monitoring-a Case Study of Die Cutting Machine. International Journal of Production Research. https://doi.org/10.1080/00207543.2020.1817999.
[139] Wang, Z., Feng, W., Ye, J., Yang, J., Liu, C., 2021, A Study on Intelligent Manufacturing Industrial Internet for Injection Molding Industry Based on Digital Twin. Complexity, 2021. https://doi.org/10.1155/2021/8838914.
[140] Werner, A., Zimmermann, N., Lentes, J., 2019, Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin. Procedia Manufacturing. Elsevier B.V.: 1743–1751. https://doi.org/10.1016/j.promfg.2020.01.265.
[141] Xi, T., Benincá, I.M., Kehne, S., Fey, M., Brecher, C., 2021, Tool Wear Monitoring in Roughing and Finishing Processes Based on Machine Internal Data. International Journal of Advanced Manufacturing Technology, 113:3543–3554. https://doi.org/10.1007/s00170-021-06748-6.
[142] Xie, R., Chen, M., Liu, W., Jian, H., Shi, Y., 2021, Digital Twin Technologies for Turbomachinery in a Life Cycle Perspective: a Review. Sustainability, 13:2495. https://doi.org/10.3390/su13052495⟨https://www.mdpi.com/2071-1050/13/5/2495⟩.
[143] Yan, K., Xu, W., Yao, B., Zhou, Z., Pham, D.T., 2018, Digital Twin-Based Energy Modeling of Industrial Robots. Communications in Computer and Information Science, 946:333–348. https://doi.org/10.1007/978-981-13-2853-4_26.
[144] Zambal, S., Eitzinger, C., Clarke, M., Klintworth, J., Mechin, P.Y., 2018. A Digital Twin for Composite Parts Manufacturing: Effects of Defects Analysis Based On Manufacturing Data, In: Proceedings - IEEE INDIN 2018, Institute of Electrical and Electronics Engineers Inc., 803–808.10.1109/INDIN.2018.8472014.
[145] Zehetner, C., Reisinger, C., Kunze, W., Hammelmüller, F., Eder, R., Holl, H., Irschik, H., 2021, High-quality Sheet Metal Production Using a Model-based Adaptive Approach. Procedia Computer Science. Elsevier B.V.: 249–258. https://doi.org/10.1016/j.procs.2021.01.162.
[146] Zhang, L., Chen, X., Zhou, W., Cheng, T., Chen, L., Guo, Z., Han, B., Lu, L., 2020, Digital Twins for Additive Manufacturing: a State-of-the-art Review. Applied Sciences, 10:8350. https://doi.org/10.3390/app10238350⟨https://www.mdpi.com/2076-3417/10/23/8350⟩.
[147] Zhang, S., Kang, C., Liu, Z., Wu, J., Ma, C., 2020, A Product Quality Monitor Model with the Digital Twin Model and the Stacked Auto Encoder. IEEE Access, 8:113826–113836. https://doi.org/10.1109/ACCESS.2020.3003723.
[148] Zhang, Z., Lu, J., Xia, L., Wang, S., Zhang, H., Zhao, R., 2020c. Digital Twin System Design for Dual-manipulator Cooperation Unit, In: Proceedings of 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference, ITNEC 2020, Institute of Electrical and Electronics Engineers Inc., 1431–1434.10.1109/ITNEC48623.2020.9084652.
[149] Zhao, G., Cao, X., Xiao, W., Zhu, Y., Cheng, K., 2019. Digital Twin for NC Machining Using Complete Process Information Expressed by StEP-NC standard, In: ACM International Conference Proceeding Series, Association for Computing Machinery.10.1145/3351917.3351979.
[150] Zhao, L., Fang, Y., Lou, P., Yan, J., Xiao, A., 2021, Cutting Parameter Optimization for Reducing Carbon Emissions Using Digital Twin. International Journal of Precision Engineering and Manufacturing. https://doi.org/10.1007/s12541-021-00486-1.
[151] Zhao, Z., Wang, S., Wang, Z., Wang, S., Ma, C., Yang, B., 2020, Surface Roughness Stabilization Method Based on Digital Twin-driven Machining Parameters Self-adaption Adjustment: a Case Study in Five-axis Machining. Journal of Intelligent Manufacturing. https://doi.org/10.1007/s10845-020-01698-4.
[152] Zheng, Y., Chen, L., Lu, X., Sen, Y., Cheng, H., 2020, Digital Twin for Geometric Feature Online Inspection System of Car Body-in-white. International Journal of Computer Integrated Manufacturing. https://doi.org/10.1080/0951192X.2020.1736637.
[153] Zheng, Y., Yang, S., Cheng, H., 2019, An Application Framework of Digital Twin and its Case Study. Journal of Ambient Intelligence and Humanized Computing, 10:1141–1153. https://doi.org/10.1007/s12652-018-0911-3.
[154] Zhuang, C., Liu, J., Xiong, H., 2018, Digital Twin-based Smart Production Management and Control Framework for the Complex Product Assembly Shop-Floor. International Journal of Advanced Manufacturing Technology, 96:1149–1163. https://doi.org/10.1007/s00170-018-1617-6.