big data and cognitive computing

Review

Digital Twins for Discrete Manufacturing Lines: A Review

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Abstract: Along with the development of new-generation information technology, digital twins (DTs) have become the most promising enabling technology for smart manufacturing. This article presents a statistical analysis of the literature related to the applications of DTs for discrete manufacturing lines, researches their development status in the areas of the design and improvement of manufacturing lines, the scheduling and control of manufacturing line, and predicting faults in critical equipment. The deployment frameworks of DTs in different applications are summarized. In addition, this article discusses the three key technologies of high-fidelity modeling, real-time information interaction methods, and iterative optimization algorithms. The current issues, such as fine-grained sculpting of twin models, the adaptivity of the models, delay issues, and the development of efficient modeling tools are raised. This study provides a reference for the design, modification, and optimization of discrete manufacturing lines.

Keywords: digital twin; discrete manufacturing; production line

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1. Introduction

With the intensification of market competition and the increasing personalized needs of customers, the global manufacturing environment is characterized by collaboration, personalization, and greening, which result in higher requirements for improving the efficiency of production and product quality and reducing production costs and resource consumption [1]. The manufacturing line is a core component of discrete manufacturing, and it has a direct impact on the products' quality, costs, the delivery cycle, and so on. It is key to improving the core competitiveness of enterprises [2]. To meet the above requirements, the manufacturing line should have the following characteristics: (1) support for multi-variety and small-batch customized production modes [3,4]; (2) multi-directional coordination of resource deployment for reducing the lag in production factors leading to mutual waiting between resources; (3) visualization of processing data to achieve fine management and precise control; and (4) multi-objective self-iterative optimization with high efficiency, high quality, and low consumption. The traditional discrete manufacturing paradigm cannot satisfy these requirements. The emergence of DTs presents a possible solution to meet the abovementioned needs.

The first terminology of DT was given by Grieves in a 2003 presentation. The National Aeronautical Space Administration (NASA) released an article in 2012 entitled "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles", setting a key milestone for the development of DTs [5]. Subsequently, DTs were studied and used by Siemens, the U.S. Department of Defense, and so on. Due to the emergence of new technologies such as the Internet of Things, big data, and artificial intelligence, DTs began rapid development in 2017.

A digital twin constructs the interactive mapping relationship between physical and virtual spaces through model simulation, real-time acquisition, historical operation, and other related data. Thus, the real-time monitoring and dynamic adjustment of the manufacturing process can be realized. Ren [6] proposed a framework for the reconstruction of production lines and intelligent monitoring of the manual assembly of customized products based on DT to solved the problems of easy misassembly and low efficiency. Xia [7] proposed a DT-based real-time energy optimization method for reducing energy consumption in production lines based on DT technologies. To solve the problematic control of production speed and optimization of the processing sequence in the welding process, Liu [8] developed a capacity evaluation and scheduling optimization system for ship components. The validation results indicated that the optimized process scheme increased production efficiency by 7.27%. Qiu [2] developed an intelligent maintenance system for a solenoid assembly line based on DT, integrating real-time process monitoring, feedback on the process of production, and feedback on the quality of production.

Despite the increasing popularity of DT research, few efforts have been devoted to reviewing the DT applications in discrete manufacturing lines. This study aimed to review the current areas of application and progress of DTs in discrete manufacturing lines, discuss the key technologies in their application, and summarize the issues and challenges.

The rest of this article is organized as follows. Section 2 reviews DTs, Section 3 discusses the relevant literature, Section 4 introduces the applications of DTs for discrete manufacturing lines, Section 5 analyzes the key technologies, and Section 6 presents the issues and challenges. Finally, Section 7 concludes the article.

2. Review of Digital Twins

Before exploring the application of DTs for discrete manufacturing lines, it is necessary to clarify the definition of a DT, its characteristics, and the differences between DTs and digital models, digital shadows, and digital threads.

2.1. Definition of Digital Twins

The original form of a DT was described as a digital information construct of a physical system, which is created as an entity on its own and is connected to the physical system [9]. With the continuous development of technology, the definition of DTs has been gradually improved. According to Saddik [10], a DT is a digital replica of a physical entity. According to Madni [11], a DT is a virtual instance of a physical system. Barricelli [12] provided 29 different definitions of DTs based on past works, eight of which were linked to works in the manufacturing application domain. Table 1 shows some definitions of DTs used in recent years. They all mentioned virtualization, interaction, and evolution.

2.2. Characteristics of Digital Twins

This subsection discusses the characteristics of DTs. Saddik [10] summarized the characteristics of DT including unique identifiers, sensors and actuators, artificial intelligence, communication, trust in the representation, privacy, and security. Barricelli [12] stated that both the physical system and the DTs must be equipped with networking devices to guarantee a seamless connection and a continuous exchange of data. According to the literature above, combined with the definition of DTs, DTs have the following characteristics: virtuality, interactivity, and artificial intelligence.

(1) Virtuality. A digital twin is a virtual information model that provides services in the form of software or platforms, which is the basis for interactions with the physical entity and is the key difference from information–physical systems [13].

(2) Interactivity. The physical entity and the DT should be able to seamlessly connect and continuously exchange data through direct physical communications or indirect cloud-based connections [12]. The digital twin not only receives the data on the environment, the physical entities, or domain experts in almost real-time, but also sends back the functional optimizations, predictions, and decisions to them in time.

(3) Artificial intelligence. A digital twin should be embedded with ontologies, machine learning (ML), and deep learning techniques to process the big data acquired and exchanged with the environment, the physical entities, or the domain experts.

Table 1. Definitions of digital twins.

Ref.	Publication Time	Definitions
[10]	August 2018	"Digital Twins are being redefined as digital replications of living as well as nonliving entities that enable data to be seamlessly transmitted between the physical and virtual worlds."
[11]	January 2019	"A digital twin is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle."
[12]	November 2019	"A DT is a living, intelligent and evolving model, being the virtual counterpart of a physical entity or process."
[14]	September 2021	"A set of adaptive models that emulate the behaviour of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system."
[15]	August 2023	"Digital Twin (DT), usually described as a virtual representation of a physical product or system connected with bi-directional data."

2.3. Classification of Digital Twins and Digital Threads

According to the level of integration of the data, DTs can be categorized as digital models, digital shadows, or digital twins [9]. A digital model is not connected to the physical entity, so no data are exchanged between them. It can be used for product designs. Only one-way real-time data communication from the physical to the digital space creates a "digital shadow", a significant application in the visualization of production. A bi-directional real-time data exchange between physical and digital space builds a DT, which can be used for scheduling production, controlling production, and predicting faults [16].

Digital twins and digital threads are sometimes understood to be synonymous [16]. A digital thread seamlessly and efficiently connects the information generated during the life cycle of a product or system, from creation to removal [17]. It provides data and information for the DT and enhances data sharing and traceability [18].

3. Statistical Analysis of the Relevant Literature

We searched for the relevant journal and conference articles that were published from 2017 to 2023 containing "digital twin" in the title and "production line", or "manufacturing line", or "assembly line", in the title or abstract, and we removed the articles about process manufacturing. In total, 57 articles were included in this research. The statistics regarding the number of various types of manufacturing lines are shown in Figure 1. There were twenty-three articles for assembly lines, six articles for machining lines, five articles for FESTO experimental lines, and five articles for unspecified lines, with toys, packaging, and brake discs being categorized as the other lines.

The areas of application studied in the literature can be classified into three categories according to the manufacturing stage: (1) optimization of the layout and balance of production lines, (2) scheduling production and process control, and (3) prediction, maintenance, and fault diagnosis. The literature on the applications of DTs for discrete manufacturing lines is shown in Table 2.

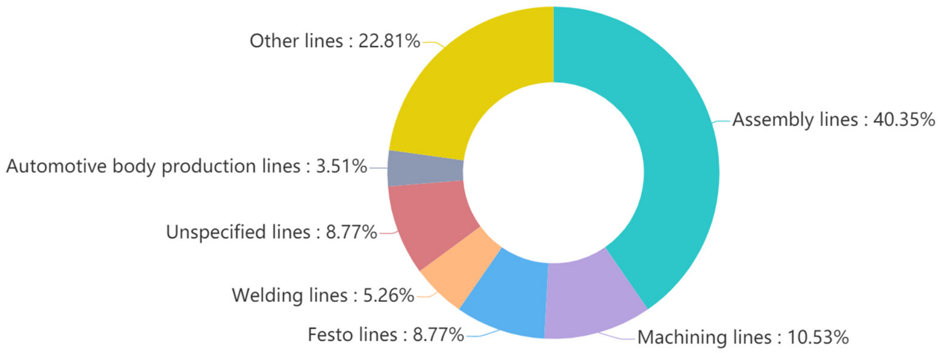

Figure 1. Statistics of manufacturing lines.

Table 2. Presentation of applications in the literature.

Application	Ref.	Comment
Planning and design, virtual commissioning	[19–24]	Optimization of the layout and balance
	[22,25]	Virtual commissioning
	[6,26–28]	Reconfiguration of production lines
Production scheduling and process control	[29–32]	Scheduling decisions
	[8,33–41]	Optimization of processing parameters
	[2,42–49]	Route planning and visualization
	[7,50]	Reducing energy consumption and the scrap rate
Prediction, maintenance, and fault diagnosis	[31,51,52]	Fault diagnosis
	[46,53]	Optimized maintenance planning
	[54]	Predicting production plans
	[48,55–57]	Predicting energy consumption or operational performance

The construction of the framework of DTs for production lines is a separate category [58–71]. The literature exploring the scheduling and control of the production process is the largest, followed by the construction of a framework of DTs. Moreover, some of the literature involves multiple areas of application [22,31,46].

4. Applications of DTs in a Discrete Manufacturing Line

The simulation model of the production line established by a DT can determine the most effective layout and process flow of the production line before implementation of production, and virtual commission can be carried out to save a huge amount of time. Real-time interactions with the physical production line during the production process through the Industrial Internet of Things (IIoT) can realize the visualization. At the same time, massive data from equipment, environment, materials, and products are generated [72]. Raw data are barely useful. They need to be cleaned before they are stored and used. Cloud services provide easy access to historical data as well as analysis without the need to deploy servers. However, it may lead to delayed delivery of data. Edge computing can reduce the latency. The analysis and mining of data through tools such as ML enables iterative optimization and adjustment of the various elements of production, prediction of the health status of the equipment, and appropriate decision-making to adapt to the constant changes in the real production environment, as shown in Figure 2.

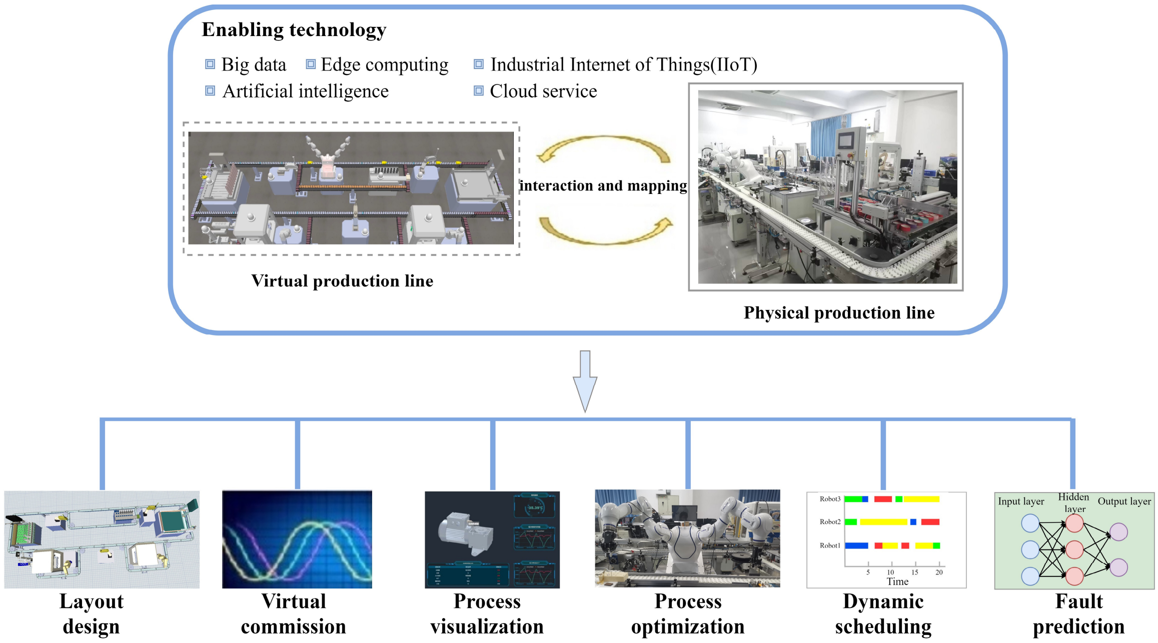

Figure 2. Application framework of DTs for discrete manufacturing lines.

4.1. Design and Improvement of Discrete Manufacturing Lines

For the planning and design stages of a production line, it is necessary to carry out layout planning, process planning, the design of the process, and the design of the control strategy for the production line. The physical production line may not exist at this stage. A production line model can be built quickly by commercialized general-purpose software. Then the optimization algorithm can be used to analyze the simulation data to obtain the optimal layout, processing parameters, etc., as shown in Figure 3. To facilitate the timely detection and resolution of problems, simulation of the production line at an early stage can verify the feasibility of the design as well as the process and manufacturing, and the simulation can also be used to improve the existing production line's layout and imbalances in production and other issues to improve the efficiency of production and utilization of equipment [19,20,23,24]. For example, Tu [23] built a simulation model of a wheelset pressing line with Flexsim to determine the "bottleneck" problem in the line and put forward optimization methods. Unlike the offline simulation above, Guo [24] used Plant Simulation to adopt a decoupling method based on the event mechanism and multi-objective optimization, which was continuously optimized in the simulation and verified in an air-conditioning production line.

In addition to commercial simulation software, we can also build our own simulation platforms. To solve the difficult problems in the early planning stage of the production line, save time during the equipment commissioning phase, and improve the visual level of the production line, Hou [21] established a DT model of the flexible manufacturing production line for brake discs with SolidWorks, CINEMA 4D, Unity 3D software, and a MySQL database to realize the simulation of the manufacturing process, optimization of the process, monitoring collisions, optimization of the robots' trajectory, and virtual-real synchronization. Wang [22] designed a DT system for a hardware production line in Demo3D software. A genetic algorithm was used to improve the process's layout, which increased the utilization of equipment. To adapt the production line to the needs of different products, other research [6,26–28] has explored the use of DTs to realize the reconfiguration of the production line.

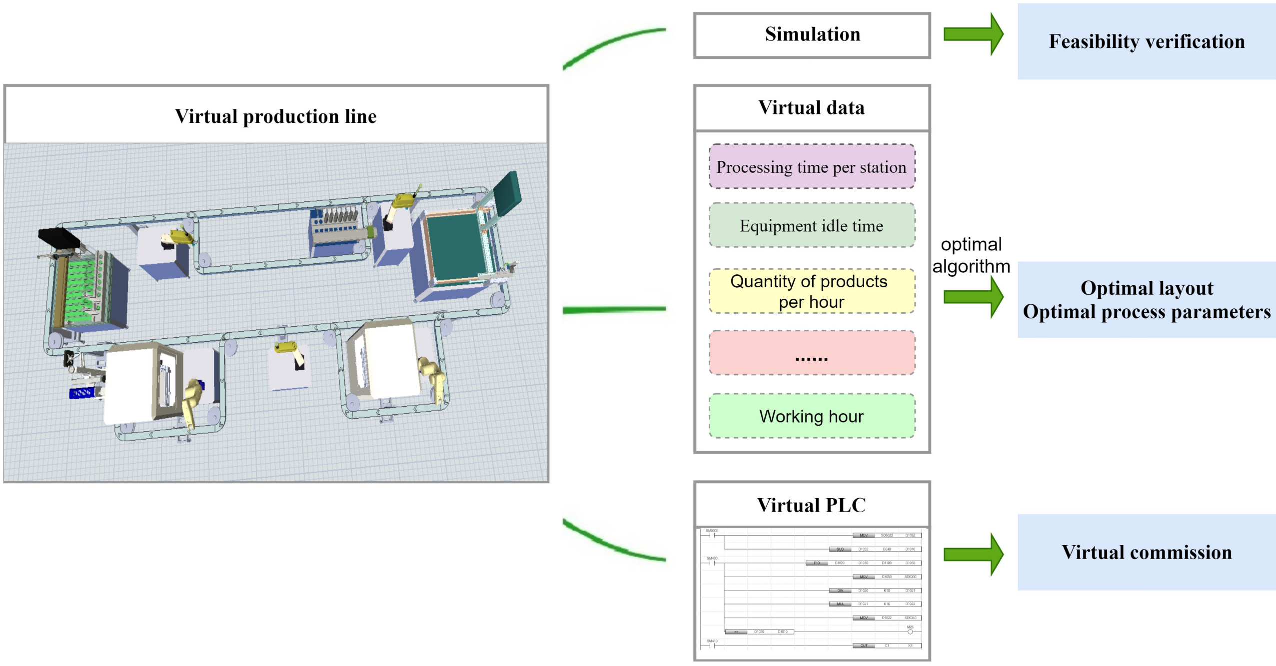

Figure 3. Digital twins for the design of production lines.

4.2. Scheduling and Control of Production Lines

4.2.1. Scheduling of Production Lines

The scheduling of production lines can be categorized into static and dynamic scheduling. Earlier researchers studied the optimization of an objective under certain conditions, such as minimizing the total completion time, assuming that the processing time is fixed [73]. In actual production, however, various situations cannot be carried out according to the original production plan; for example, through equipment failure, absent workers, scrap parts, raw material shortages, early delivery, or insertion orders [74]. Therefore, a timely response to dynamic events in scheduling the production job shop becomes an important problem that needs to be solved urgently [75]. Digital twins, which have the characteristics of virtual reality mapping and interactive fusion, provide a new way of solving scheduling problems in smart manufacturing, and they can generate new scheduling plans by building production scheduling models and scheduling algorithms, as shown in Figure 4. To resolve the dynamic disturbances in the assembly process, Shen [30] established a DT-based bearing assembly planning model and proposed a task rescheduling strategy for a robotic assembly line. Villalonga [29] presented a framework for decentralized and integrated decision-making for re-scheduling of a cyber-physical production system, and the validation and proof-of-concept of the proposed method was conducted in an Industry 4.0 pilot line of an assembly process. The experimental results demonstrated that the proposed framework was capable of detecting changes in the manufacturing process and making appropriate decisions for re-scheduling the process. Table 3 shows the scheduling case studies.

Table 3. Presentation of scheduling case studies.

Ref.	Algorithm	Real-Time Interaction	Source of Disturbance
[73]	Variable local search algorithm	/	/
[74]	Heuristic algorithm	/	Simulated
[75]	Fast nondominated sorting genetic algorithm	CPS	Physical
[29]	Genetic algorithm	OPC-UA	Physical
[30]	Adaptive discrete bees algorithm	CPS	Simulated

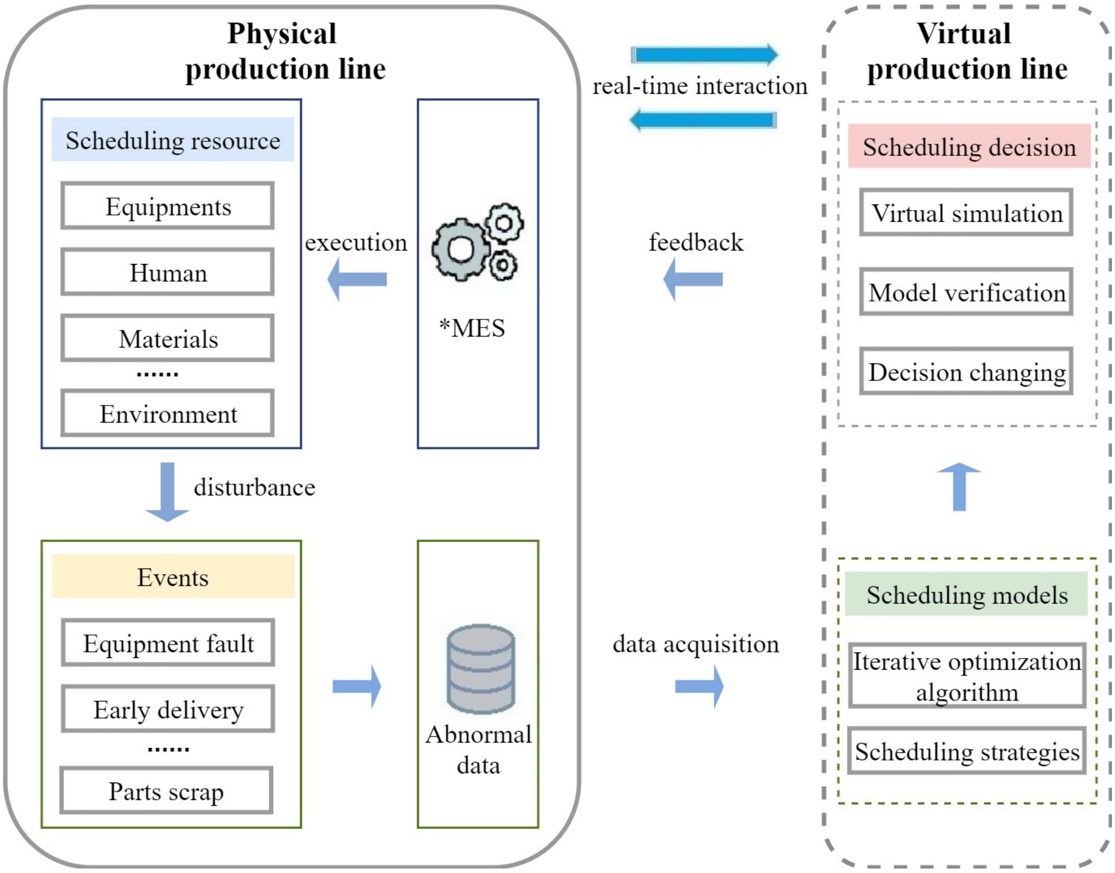

Figure 4. Digital twins for scheduling. *MES, manufacturing execution system.

4.2.2. Visualization and Quality Control of Production Lines

Traditional management of production lines faces the "black box" problem, and there is a lack of intuitive and effective methods for obtaining important information, such as the status of on-site equipment and the progress of the program's execution. The visualization of the DT model can show the structure, parameters, and process of the constructed model, providing support for the visual management and monitoring of the model [76]. Oriti [43] digitalized all of the technologies offered in the physical line for assembling skateboards in a DT successfully via the SteamVR plugin embedded in Unity 3D, allowing visualization, navigation, and inspection of the line through virtual reality.

Timely adjustments can be made to improve the products' quality by storing, analyzing, and calculating the large amount of production data collected. First, a high-fidelity model of the key components of the production line needs to be established, such as the establishment of a high-fidelity model of the cutting tools, to ensure the accuracy of the machined parts. Then the data are analyzed, and the features are extracted to establish a process database that affects the products' quality. The optimal processing parameters can be obtained by iterative optimization algorithms. Finally, the optimal processing parameters are implemented in the physical production line to control the products' quality, after simulation and verification by the twin model, as shown in Figure 5. Zhang [33] designed a new intelligent production line for automotive MEMS pressure sensors driven by a DT, and the real-time online monitoring and regulation of the products' quality was realized by establishing a database of the key processes. Liu [38] proposed a cloud-edge-based DT system (CEDTS) with a four-terminal-architecture. With the implementation of the CEDTS, the range of fluctuation of geometric errors of the machined parts was reduced significantly. To solve the optimization problem by considering data on the overall quality of assembly, Ma [41] introduced a data-driven quality control model.

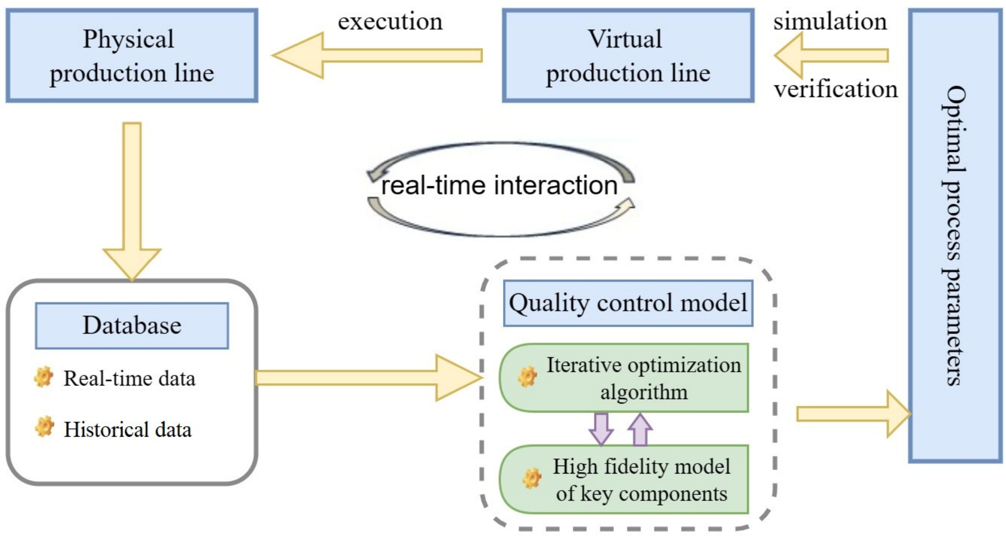

Figure 5. Digital twins for quality control.

4.3. Fault Prediction and Maintenance of Critical Equipment

Predictive maintenance (PdM) is the most widely used maintenance strategy [77]. A digital twin for PdM enables accurate recognition of the equipment's status and proactive fault prediction. This shift from reactive to proactive services optimizes maintenance schedules, minimizes downtime, and improves an enterprise's profitability and competitiveness [78]. Dinter categorized the DT abstraction layer for predictive maintenance into three levels: components, systems, and systems of systems. Here, a component could be a bearing or a pump, and a system can be a gearbox or engine, while a system of systems may represent a shop floor or a fleet of airplanes [79], as shown in Figure 6 below.

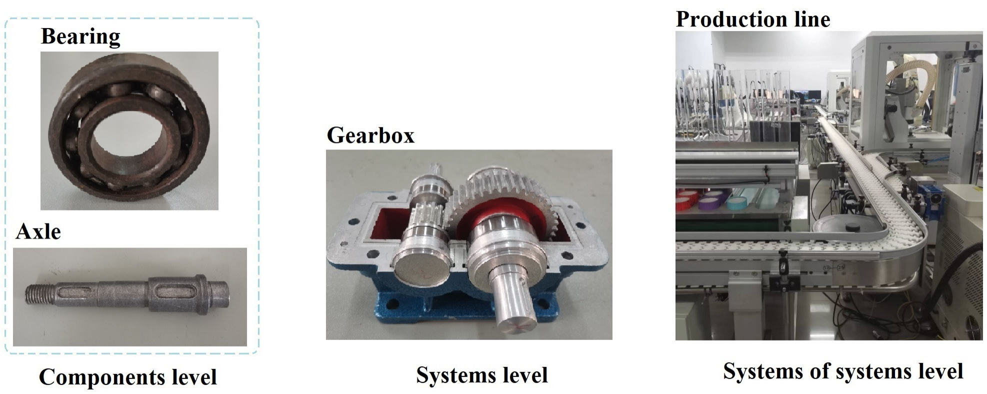

Figure 6. The DT's abstraction layers for predictive maintenance were categorized into three levels.

Tao et al. [80] were the first to introduce prognostics and health management using DTs by constructing a fault prediction model with the extreme learning machine (ELM) and applying it to a wind turbine gearbox. Booyse [81] found that a DT model created using a generative adversarial network was significantly more sensitive to deviations from healthy behavior compared with one created using the variational auto-encoder for a synthetic gearbox dataset. Realistic experiments on bearings were conducted. Using the LASOO, SVR, and XGBoost algorithms, models for predicting the axle's temperature and speed were designed to develop an optimal maintenance strategy [82]. Liu [83] proposed a "super-network-warning features" method of fault prediction and maintenance based on DT technology. This method was compared with the traditional method on an aero-engine bearing. It supplemented the missing link between fault prediction and maintenance. Toothman [84] presented a DT-based framework for reusing modeling resources. The framework's standardized DT classes and aggregation relationships allowed component-level models to be re-used and aggregated to predict faults in the pump's bearing system.

System-level DT aims to perform predictive maintenance on a full machine [79]. Moghadam [85] presented a DT-based approach to condition monitoring for drivetrains on floating offshore wind turbines that uses estimated parameters for automated fault diagnosis and prognosis. There is the question of whether system-level predictive maintenance is a combination of component-level overlays. Luo [86] supposed that, due to the complexity, change over time, and nature of coupling in CNCs, predictive maintenance should be conducted at the system level of interactions rather than at the component or part level. Therefore, unlike the component level, where a data-driven DT is mostly used, predictive maintenance at the system level requires more of a hybrid model-driven and data-driven DT.

Xu [52] presented a two-phase digital-twin-assisted fault diagnosis method using deep transfer learning (DFDD), which realized fault diagnosis in both the development and maintenance phases. This method was used in a car body-side production line, and this was a case of predictive maintenance of the system of systems.

The application of a hybrid model-driven and data-driven DT for fault prediction is shown in Figure 7. After the fault prediction model is trained with historical data, the real-time data of physical equipment are inputted to predict the state of the equipment. If the predicted data are abnormal, the corresponding maintenance plan will be inputted into the virtual model for simulation, verification, and evaluation. Finally, a maintenance plan is generated to realize PdM.

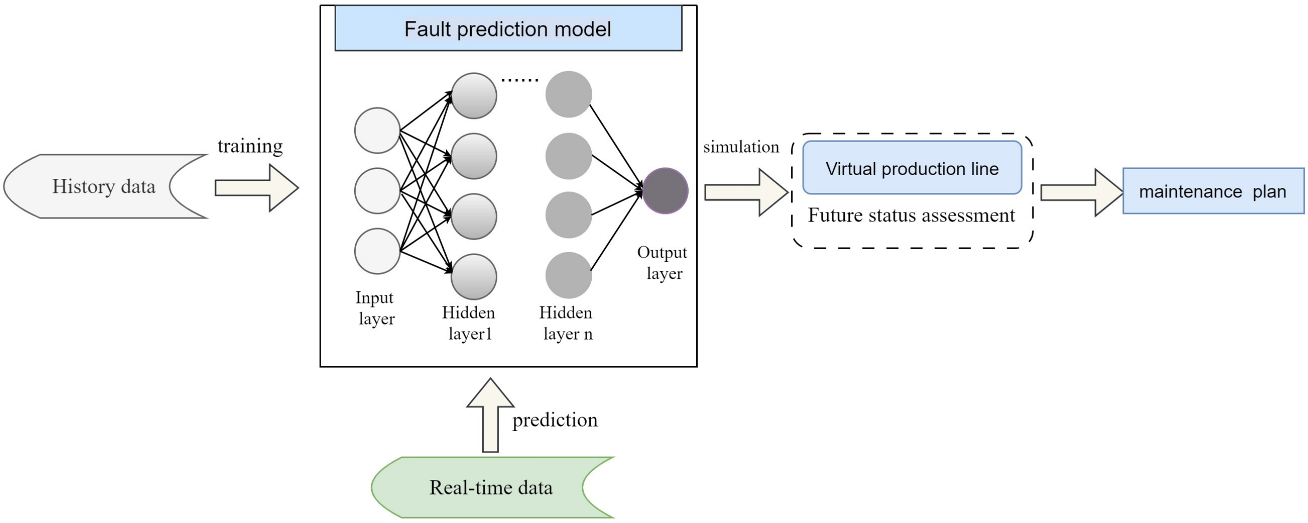

Figure 7. The application of a hybrid model-driven and data-driven DT for fault prediction.

5. Key Enabling Technologies

A DT should not only reflect the state of the physical production line in the virtual space but also provide an effective method of the production line's optimization, scheduling, maintenance, fault prediction, and so on. The realization of these functions involves the following key technologies.

5.1. A High-Fidelity DT Model of the Production Line

The model is an important component of the DT and is an important premise for the realization of the DT's functionality [87]. The key technical difficulty in the application of DT technology in the manufacturing field is establishing a multi-dimensional fusion model that realistically simulates and reflects physical entities [76]. For example, the Beijing-based power company BKC Technology struggled to work out that an oil leak was causing a steam turbine to overheat. It turned out that lubricant levels were missing from its DT [88].

Through high-fidelity digital models, management of the whole life cycle from design and simulation to manufacturing and maintenance was realized. Tao [89] proposed the construction of a model including four dimensions: geometry, physics, behavior, and rules; and the techniques and tools used for modeling were summarized as shown in Figure 8 below.

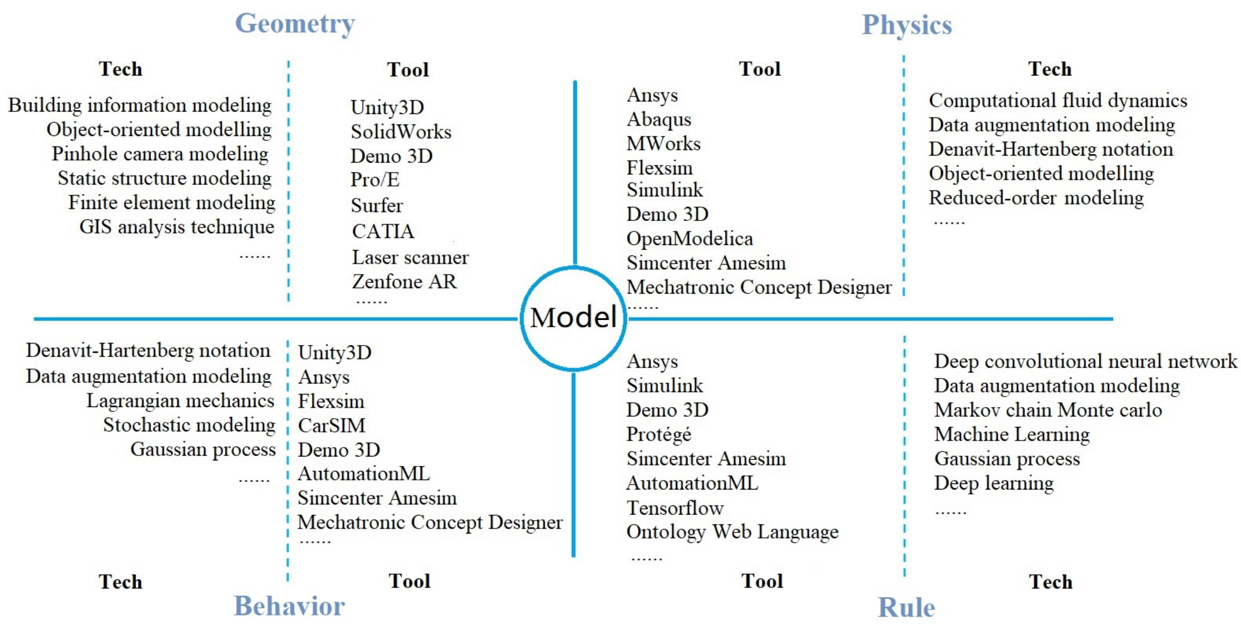

Figure 8. Framework of technologies and tools in used construction of a model [89]. Reprinted with permission from ref. [89]. Copyright 2022 The Society of Manufacturing Engineers. Published by Elsevier Ltd.

The construction of a geometric model delineates the shape, size, internal structure, spatial position and attitude, and assembly interfaces of physical entities. A geometric model is not only for shaping, but its structural integrity and the accuracy of its data also underpin the motion analysis, optimized design, virtual interaction, and the like. Therefore, the geometric model's fidelity is crucial for construction of the geometric model [89].

By integrating cyber models into the DT model, Xie [90] accurately mapped the status of tool wear through digitalization of cutting tools. However, the greater the detail, the slower the simulation. Therefore, an area of concern is the use of appropriate simplification methods for the model to achieve high-fidelity representation of physical entities with smaller transfer files.

Construction of a physical model provides the basis for services such as quality control and the analysis and prediction of the physical properties [89]. Xiong [91] proposed a scheme for predicting degradation for trains' electropneumatic valves under thermal stress based on a high-fidelity DT model with a parameter-updating ability.

A behavioral model is constructed to represent the sequential, concurrent, linked, periodic, and random behaviors of physical entities. Construction of the rule model unveils implicit knowledge and portrays the evolutionary trends and patterns of physical entities [89].

The modeling of critical equipment is the beginning of high-fidelity modeling of production lines. Xie [92] addressed the problem of low accuracy in the feed twin system, which directly determined the dimensional accuracy of machining commutators by modeling the following error through ML algorithms and neural networks; predicting the actual response outputs of the feed system at different positions, speeds, and accelerations; and making corrections to the twin model to improve the fidelity of the DT model of the feed system.

5.2. Interaction with Real-Time Information

Models resemble the skeleton of the DT system, while data are its lifeblood [93]. The interaction with real-time information [94] provides conditions for visualization of the production process, dynamic updating of DT models, real-time control of physical entities, and online optimization of decision-making regarding solutions [95]. Li [96] reconstructed the 3D graphic model of a robotic assembly with a 3D depth sensor. During the interaction, the virtual contact force derived from the geometric and contact dynamics models was generated in real time, and the object's deformation was rendered. To accurately determine the clamping force and positioning, another study mapped the real-time acquisition of data from pressure sensors and the workpieces' geometry into a model [35]. Other research fused real-time data from vision and force sensors to algorithms to realize the assembly of robotic peg-in-hole systems and built an online monitoring DT system to predict the risk of a collision [42]. Both of these studies [35,42] realized real-time control of physical entities through real-time interaction.

Ye [97] successfully transferred the data of a doffing robot and winder to the Unity3D platform through the S7.NET component, and then used the co-processing mechanism to directly transfer the data to the specified attributes of the doffing robot and winder to update the state, which greatly improved the real-time element. Xie [51] adopted the principle of function–preference pairing of virtual–real variables to improve the response speed of the DT model and to reduce the state delay between the physical entity and the DT model. That is, variable signals at key nodes were selected as the carriers of information on virtual–real interactions, while signals at the other nonkey nodes were not used as listening objects. Processing of the collected data is also an important factor that affects interactions with real-time information. In one study [67], the multi-source heterogeneous information processing system unified the discrete segmentation information into abstract JSON data through an artificial intelligence neural network model, and the result of the similarity judgment was obtained via the sample training. Information research and judgment related to production lines were carried out through the training model, which greatly reduced the network's delay and the data blocking caused by data processing.

The use of edge computing can improve the real-time response compared with cloud computing [29]. Extreme wireless connectivity can be provided by 6G networks to meet the requirements of ultra-high throughput and ultra-low latency for short-range communication [98] and fuel the future development of DT applications in smart manufacturing.

5.3. Iterative Optimization Algorithms

Iterative optimization algorithms can achieve the optimization of production lines, fault prediction and maintenance of equipment, and other functions with the help of massive field production data obtained by the DT. Iterative optimization algorithms are the core of DTs. Each algorithm has its advantages and disadvantages, and the choice of which algorithm is related to the application of the scene, the realization of the goal, and other factors.

Heuristic algorithms have the advantage of global optimization, of which the genetic algorithm is the most widely used for the optimization of systems [19,22,24] as well as scheduling decisions [29,31]. Guo [24] proposed a multi-objective optimization including optimization of the layout, processing capability, logistics, and test equipment. Another study [7,8] used an improved genetic algorithm with the goal of minimizing the consumption of time and energy. Other research [39] used a real-coded genetic algorithm to improve the geometrical quality of each assembly. Other heuristic algorithms have been used. Shen [30] proposed the Adaptive Discrete Bee Algorithm to optimize the assignment of assembly tasks and provide feedback to the physical robotic assembly line. The ant colony algorithm was proposed [25] to optimize the allocation of cargo space in an automated three-dimensional warehouse, and an improved seagull optimization algorithm [38] and the gray wolf optimizer algorithm were used [56].

Another study [80] used ELM, which is a single-hidden layer feed-forward neural network with a fast learning speed and good generalization performance, to predict the cause of faults in a gearbox [79]. With the poor dynamics of the ELM algorithm, other work [57] proposed an online ELM algorithm to construct the prediction model for the performance of a robotic production line. The above are cases of the application of ML algorithms. As a subset of ML algorithms, deep learning algorithms have superior performance to other ML algorithms [4]. Deep neural networks (DNNs) can discover intricate structures and extract high-level features from massive data [99]. Many studies have taken advantage of DNNs for monitoring mechanical health. Deep neural networks often perform well when the training data and test data follow the same distribution. However, it is difficult to obtain sufficient fault data for training the diagnostic model, as the equipment is often in a healthy state. Thus, the DFDD was proposed [52].

Reinforcement learning (RL) is an important branch of ML which tries to explore the optimal policy for decision-making problems through continuous interactions with the environment [100]. The Deep Q network (DQN), a combination of RL and DL, has achieved excellent success under various convoluted circumstances and tests. A study [100] used the DQN to implement the assignment of tasks. However, the DQN can only deal with discrete, low-dimensional motion spaces, whereas tasks such as assembly with 6R robots have high-dimensional continuous motion spaces. Thus, another study [42] used the deep deterministic policy gradient to train a robot in a production line with fault-tolerant and corrective capabilities for unknown situations. In one study [59], the profit-sharing-based DQN algorithm was applied to the problem of optimizing range-inspection control in the DT of an automated conveyor system with significant optimization effects on the robustness, convergence rate, and stability compared with the test of performance with DQN. The maintenance problem of the last machine in an assembly line using the average reward DQN has also been studied [53].

6. Issues and Challenges

Benefitting from the development of artificial intelligence, big data, the Internet of Things, cloud computing, and other information technologies, DT research has seen explosive growth since 2017 [101], but it is still in its infancy, and its application to discrete manufacturing lines still faces many issues.

6.1. Fine-Grained Sculpting of Twin Models

Due to the complexity of a production line's structure, it is difficult to achieve complete physical modeling and multi-scale detailed representation in the real-time physical modeling solution [102]. Most of the commercial tools provided by different vendors only allow one to perform simulations of the equipment with a very high level of abstraction or with the use of statistical approximations [103], which are not yet able to portray resources at different levels of granularity. This problem is particularly acute when the DT needs to integrate multiple tasks, such as dynamic reconfiguration and fault prediction, at the same time.

Centomo [103] proposed a DT design methodology enabling multi-level simulation of the equipment in a manufacturing plant that allowed it to switch from one model to another to obtain simulation strategies with different granularities of synchronization. This method provides ideas for multi-granularity modeling of production lines. Wang [104] proposed a knowledge graph (KG)-based method of multi-domain model integration for digital twin workshops. In this architecture, the model's ontology can contain self-defined multi-domain models and construct knowledge models that meet the granularity of the operation's requirements. The granularity scale of the twin model largely determines the performance of the system, and the problem of how to realize the fine-grained scaling of critical equipment still needs to be solved.

6.2. Adaptivity of Twin Models

A production line is a physical entity that changes, and for the DT to always run at a high-performance level, the virtual entity should be able to automatically update and make new decisions based on the physical entity or changes in the system without human intervention; that is, the DT should have adaptive capabilities. Specifically, this includes autonomous perception, replicability, and composability. The DT must be capable of discovering the available physical objects present within the execution environment and consequently handle the communication and interactions according to the supported protocols and data formats [105]. One study [106] presented ML methods to enhance the cognitive capabilities of the Industrial Internet of Things (IIoT) so that the edge-intelligent IIoT was expected to act in a similar manner to tentacles to perceive changes at the network's edge. At the same time, the corresponding virtual entities were also mapped in the DT; that is, the DT was replicable. The DT should be able to decouple and recombine in case of failure of a physical entity or a DT.

The self-adaptivity of a DT puts many requirements on the framework of the twin model and AI algorithms, and although there have been some attempts at adaptivity [107], there is still a big gap between them and practical applications. These are the expectations for the future of DTs.

6.3. Time Delay Issue

A digital twin needs to perceive changes in physical entities in real time to make appropriate decisions and realize the control of physical entities through actuators. Delays can cause data losses or instability in the system, and even lead to the DT's failure. The delay may come from the sensors' inputs, and network control systems (NCS), etc. The delays in NCS include processing delays, queuing delays, transmission delays, and propagation delays. Baillieul and Antsaklis referred to delays as unavoidable and one of the challenges of modern networked control systems composed of heterogeneous systems and applications [108]. Random delays exist in both sensors and NCS, and are more difficult to deal with than constant delays. A production line is a complex system and needs to transmit and control a large number of signals in real time. The problem of delays has become more prominent.

6.4. Efficient Modeling Development Tools

General simulation software that supports the modeling of production systems, such as FlexSim, Plant Simulation, Witness, Visual Components, and so on, provide a variety of built-in components, rich interfaces, and optimization algorithms that enable engineers to build models of production systems through the scripting language provided by the software to solve the problems of the production line's layout, balancing the line, scheduling, and optimization of scheduling. However, they are unable to help in management of the equipment's health and fault prediction because they lack a comprehensive portrayal of physical entities, such as the wear of tools in the turning process, the growth of cracks in gears under stress, and so on.

According to Tao [89], constructing geometric, physical, behavioral, and rule-based models and then assembling and fusing them and combining them with algorithms can make the models more functional, but with poor generalizability. The dilemma faced by DTs is that each model needs to be started from scratch, which greatly increases the modeling cost. There is an urgent need to develop a modeling technology system and an integrated software toolkit or platform. As a result, researchers can perform DT modeling at minimal cost and enable maximum access to the corresponding service provided by high-fidelity DT models [89].

7. Conclusions

This article provides a systematic review of over 50 previous publications related to the application of DTs to discrete manufacturing lines. The main contributions of this study are summarized as follows.

(1) It summarizes the current research progress on the implementation of DTs, including the design, optimization, and prediction of production lines.

(2) It outlines the key enabling technologies for high-fidelity DT models of production lines, real-time interaction with information, and iterative optimization algorithms. The related methods are described to provide a reference for researchers.

(3) It discusses the current issues, including the fine-grained sculpting of twin models, adaptivity, time delays, and efficient modeling tools. These are all issues to be addressed in the future.

This study will contribute to the further development of DT applications in discrete manufacturing lines.

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