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Artificial intelligence enhanced interaction in digital twin shop-floor

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Abstract

As an enabling technology for smart manufacturing, digital twin has been widely applied in manufacturing shop-floor. A great deal of research focuses on the key issues in implementing digital twin shop-floor (DTS), including scheduling, production planning, fault diagnosis and prognostics. However, DTS puts forward higher requirements in terms of real-time interaction. Artificial intelligence (AI), as an effective approach to improve the intelligence of the physical shop-floor, provides a new method to meet the above requirements. In this paper, a framework of AI-enhanced DTS in interaction is proposed. AI-enhanced DTS improves the real-time interaction through predictive control. The implementation mechanism of AI-enhanced interaction in DTS is also presented in detail. Enabling technologies for interaction in DTS are introduced at last.

Keywords: digital twin shop-floor (DTS); artificial intelligence (AI); real-time interaction

1. Introduction

Currently, smart manufacturing serves as an innovation to meet the changing requirements of industry, which has great advantages in reducing energy consumption, improving production efficiency and operation safety [1,2]. Shop-floor, as a typical manufacturing scenario, provides equipment and sites for various manufacturing activities. The efficiency and safety of the physical shop-floor have an important influence on production quality and manufacturing efficiency.

As an enabling technology of smart manufacturing, digital twin (DT) has attracted lots of researchers to explore its applications [3]. By bridging the physical and virtual spaces, DT mirrors the real-time states of physical objects in the virtual world and then makes the optimal decisions to optimize the manufacturing process [4]. Digital twin shop-floor (DTS) consists of the physical shop-floor, virtual shop-floor, service system, data and interaction [5]. Physical shop-floor executes the actual manufacturing activities and transmits real-time data to the virtual shop-floor [6]. Physical shop-floor includes equipment (such as robots, AGVs, machines tools, etc.) and workers. Workers in the physical shop-floor can assist in completing complex manufacturing tasks and making rapid reactions for emergency situations [7]. Virtual shop-floor driven by real-time data describes the geometry, data relationship and internal mechanism of the physical shop-floor [6] Data in DTS contains the physical data collected from the shop-floor, simulation and operation data of the virtual model, as well as the information and knowledge of the shop-floor stored in the service system [8]. Service system provides the various applications such as scheduling [9,10], production planning [11,12], fault diagnosis and prognostics [5,13]. Interaction ensures the real-time connection between the physical and virtual spaces [14].

However, there exist some significant issues in DTS. For data, the quality of data plays an essential role because it has a vital impact on the performance of DTS. DTS collects multi-source data from the physical shop-floor. The virtual model is

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driven by physical data to achieve real-time mapping. Therefore, DTS requires to acquire all relevant data from the physical shop-floor, and the collected data are required to be accurate. Otherwise, the virtual model would fail to realize realistic simulation, and then produce some errors. Furthermore, multi-source data should be processed into a unified format to meet the requirements of data fusion. Based on storage technology, transmission technology, transmission technology and fusion technology, DTS better processes the collected data and extracts useful information [6,8], which can tackle the above issues.

Regarding the problems of modeling, the high-fidelity virtual model should describe both internal mechanisms (i.e., technological process, and equipment operation mechanism) and data relationships (for example, equipment fault analysis, and product quality traceability). An effective method is to build a fusion model considering both internal mechanisms and data relationships using a hybrid algorithm, which combines the mechanism model and statistic model [15]. In a physical shop-floor, the performances of the physical objects will change along with long-time usage. It means an increasing deviation between the virtual model and physical state, which brings out inaccurate models and incorrect decisions. Accordingly, DTS should perceive the deviation and update model parameters [16].

In terms of interaction, the interaction consistency between the physical space and virtual space is quite vital. DTS should accurately evaluate the overall states of the physical shop-floor and then make corresponding control strategies to optimize the manufacturing process. Therefore, DTS requires the real-time interaction to make accurate decisions. The interaction consistency, ensuring synchronization between state perception and control execution, is particularly important, as inconsistencies would lead to delays in both perception process and control process. Although some researches provide effective approaches to solve the data and model problems, the methods to tackle the issues of interaction synchronization in DTS are sparse.

As a technical science of making machines think and behave rationally like human beings [17], artificial intelligence (AI) has been widely applied to solve specific manufacturing issues, including scheduling [18], assembly [19], fault diagnosis and prognosis [20]. As such, in this work, an AI-enhanced DTS method is proposed to tackle the issues in interaction.

The reminder of this article is organized as follows. Section 2 analyzes the key challenges of interaction in DTS from three perspectives. To address the challenges, Section 3 introduces the role of AI in the shop-floor. Section 4 presents a framework of AI-enhanced DTS in interaction and the implementation mechanism in detail. Enabling technologies for interaction in DTS is presented in Section 5. Finally, Section 6 summarizes this article and points out the future work.

2. Key issues for interaction in DTS

DTS, realizing real-time interaction between a physical shop-floor and the virtual one, aims to merge all relevant data and provide intelligent services driven by real-time data [6]. However, how to realize real-time interaction is a key problem to implement DTS.

Based on the connection between the physical space and virtual space, interaction emphasizes real-time exchange of information. Efficient interaction in DTS supports two-direction information flow. The direction from the physical space to virtual space transmits physical information, which mainly includes equipment conditions, material characteristics, environment state and other physical data. The opposite direction from the virtual space to physical space mostly sends control commands. Based on the information, DTS evaluates the status of the physical shop-floor and generates control commands to adjust the production process. Due to the dynamic changes of the physical shop-floor, DTS should acquire real-time data to accurately analyze the physical states and then makes correct control commands. Similarly, control commands should also be transmitted to the physical shop-floor in real-time to achieve the precise control. Once there exists severe interaction delay, both perception process and control process would make incorrect decisions, which has an adverse impact on the efficiency of DTS. Therefore, the key issues in interaction can be summarized from three aspects, namely, state assessment, control strategy and interaction consistency.

1) *State assessment*. To achieve effective interaction, it is necessary for DTS to accurately recognize physical objects and assess the overall state of the physical shop-floor. The data collected from the physical shop-floor usually describes the specific parameters of equipment, such as the speed of robots, materials' locations and human activities. These figures fail to describe the overall situation of the physical shop-floor. Therefore, DTS should evaluate the integrated state of the physical shop-floor based on the collected data. There exist two specific problems for state assessment. One problem is that how to recognize the current state and predict the future status of complex equipment such as robots, AGVs and machine tools. Another problem is the comprehensive evaluation of the physical shop-floor. Physical shop-floor contains various physical objects in different production states such as AGVs for transporting materials, running machines, and individuals. A correct comprehensive evaluation considered these elements is quite vital for the optimal decision-making.

2) *Control strategy*. After evaluating the current state of the physical shop-floor, DTS optimizes the production process through appropriate controls, which is also regarded as another key problem for interaction. In an autonomous shop-floor, the control strategy properly assigns tasks to different equipment to improve production efficiency. In a human-machine collaborative manufacturing shop-floor, the control strategy needs to consider not only machine efficiency, but also human tasks. On the one hand, compared with the production plan, the production schedule will have some deviations. For instance, the production schedule is ahead or behind the plan. The control strategy generated by DTS is required to consider the dynamic trend and adjust the real-time schedule. On the other hand, the physical shop-floor contains workers, robots with different functions, AGVs, and other different equipment. Due to different operation mechanisms, the equipment has different behaviors as well as responses. Workers have great flexibility in the shop-floor, therefore, unpredictive human activities also influences decisions on manufacturing task. Considering the various reactions from both equipment and workers, DTS

enables collaborative control of various components throughout the physical shop-floor, which also poses a challenge to control strategy.

3) *Interaction consistency*. A more challenging issue about interaction is ensuring the interaction consistency, which means synchronization between physical responses and control commands. The interaction consistency of DTS contains two directions, namely, perception from the physical shop-floor to the virtual one and control in the opposite direction. The former is related to real-time evaluation of the physical shop-floor. Once there exists a delay in the perception, DTS analyzes the previous state rather than the current state. Accordingly, DTS generates a delayed control which aims to the previous situation. In contrast, if the control process is delayed, the physical components would receive inaccurate commands to control the previous situation, although DTS accurately perceives the current status.

In conclusion, the problems in state assessment, control strategy and interaction consistency have adverse impact on interaction in DTS. These problems lead to the low accuracy and efficiency of interaction.

3. Artificial intelligence in shop-floor

AI is a technical science that aims to make machines think and act like human beings [17]. It is a large field that includes machine vision, machine learning, domain knowledge and other technologies.

AI has been widely applied in manufacturing shop-floor to solve various issues. To extract useful information contained in the images, machine vision enables machines to recognize, perceive and understand the physical world through vision [21]. Through processing images, manufacturing systems acquire useful information including locations of mobile equipment and materials. Therefore, machine vision is used to solve the problems in terms of object positioning, target recognition, motion tracking and condition monitoring during the whole production process [22].

Natural language processing studies the theory and method of the communication between machines and human beings, which enables machines to understand the meaning of human language. In the physical shop-floor, combined with natural language processing technique, manufacturing systems can recognize requests, commands or inquiries in voice without keyboard command input [23,24]. Workers can input relevant data into manufacturing systems in speech to improve production efficiency and shorten the response time.

In the physical shop-floor, planning algorithms are widely used to generate optimal schemes or decisions in terms of production planning, scheduling, assembly, logistics and other services. For example, to solve assembly problems, genetic algorithm, ant colony optimization and local search strategies are applied to search for feasible solutions [25]. In production planning and scheduling, genetic algorithm and tabu search are commonly used to search solutions of optimization problems [26]. These algorithms provide efficient methods for solving planning problem.

Machine learning adaptively obtains experience and knowledge from the collected data [27]. By analyzing data features and relationships among variables, machine learning extracts useful information and develops statistic models for numerous applications [28]. Machine learning has gained increased traction being adopted in fault diagnosis [29], decision-making [28], production planning [30] and other services. After collecting production data from the physical shop-floor, machine learning is utilized to extract data features. Some sensitive features are selected from the extracted features in order to remove redundant information. Machine learning is also used to establish models that describe the relationships between the selected features and target parameters. According to the relation models, manufacturing systems can accurately predict the target parameters such as equipment lifetime, production results, and energy cost, which fertilizes to generate decisions.

Therefore, combined with AI, DTS can efficiently tackle the interaction issues. Through cameras positioned in the physical shop-floor, machine vision system monitors the real-time state. AI-enhanced DTS evaluates the overall state of the physical shop-floor based on the predictive values generated by the neural network. After state assessment, AI-enhanced DTS uses genetic algorithm to develop control strategy. Moreover, the neural network can accurately predict the future situations based on the real-time data and historical data, which provides an effective method to realize the synchronization between physical responses and control commands.

4. Framework of AI-enhanced interaction in DTS

Interaction in DTS ensures real-time data exchange between the physical and virtual spaces. It contains two-direction data flow, namely, perception process and control process. The interaction mechanism of AI-enhanced DTS is shown in Fig. 1. Based on AI, DTS can evaluate the overall state of the physical shop-floor and achieve the precise control. AI-enhanced DTS also effectively proposed a new method to solve the problem caused by time delay, thus ensuring interaction consistency. In this section, implementation mechanism of AI-enhanced interaction in DTS is further illustrated from the above three aspects.

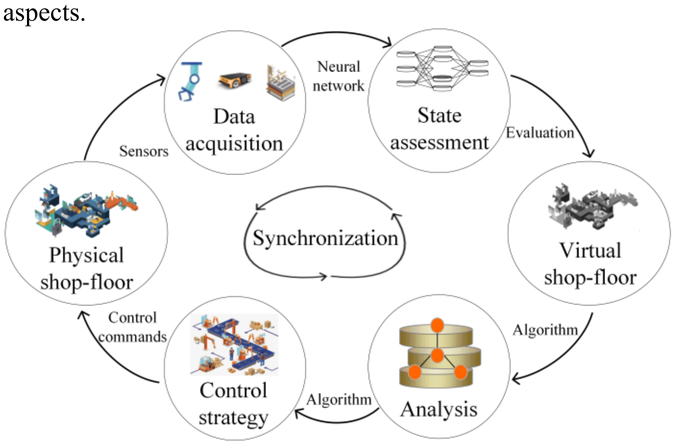

Fig. 1. Framework of AI-enhanced interaction in DTS

4.1. State assessment

In a physical shop-floor, equipment automatically executes manufacturing tasks according to control commands. For complex or flexible tasks, workers in the shop-floor can assist in completing them. Therefore, the state of the physical shop-floor contains the conditions of equipment as well as workers. To accurately perceive the current state, AI-enhanced DTS acquires data from sensors such as cameras, RFID, temperature sensors, etc. Cameras in AI-enhanced DTS are applied to capture workers' activities so that AI-enhanced DTS can make correct responses to propulsion manufacturing process as well as ensure manufacturing safety. After the image is acquired, machine vision processes the original image including filtering noises and correction. Then, it separates the target objects from the entire image and extracts image features. Subsequently, AI-enhanced DTS classifies image features and recognizes the activities based on algorithms such as support vector machine.

Moreover, AI-enhanced DTS also supports to recognize voice commands. Based on natural language processing, AI-enhanced DTS extracts useful information from voices. Before executing the voice commands, AI-enhanced DTS judges the command accuracy and evaluates its results. Once the evaluation indicates that commands bring negative impact such as reducing productivity or increasing operational risk, AI-enhanced DTS would remind operators of the adverse influence. Combined with machine vision and natural language processing techniques, DTS is able to collect data in different ways. Due to technical limitations, standards or other requirements, some shop-floors are not available to use images and voice. For these shop-floors, AI-enhanced DTS could acquire the relevant data through sensors. Based on data collection, AI-enhanced DTS constantly acquires physical data such as robots' speed, AGVs' position, environment parameters, etc. For some difficult-to-measure data (i.e., the internal temperature of running machines), AI-enhanced DTS could combine soft sensing technique to calculate them. In addition, AI-enhanced DTS collects multi-source data from different physical objects, which may include inaccurate data, conflicting data and redundant data. Before using these data, AI-enhanced DTS establishes semantic rules or data statistical models to detect and clean abnormal data.

In terms of the overall evaluation of the physical shop-floor, AI-enhanced DTS builds the prediction model with neural network to calculate future states and assess working situations. The virtual shop-floor describes the current state of the physical shop-floor, which is driven by real-time data. Based on the real-time data, historical data, and relevant knowledge, AI-enhanced DTS makes accurate predictions of the shop-floor equipment. To build and train prediction model, AI-enhanced DTS chooses the recent historical data as the sample data. Meanwhile, AI-enhanced DTS constantly collects real-time data from the physical shop-floor and uses these collected data to update the sample data. Therefore, the prediction model can reasonably predict the future characteristics of the equipment (such as efficiency, wear, vibration, temperature, etc.) based on the latest data. Bases on these data, AI-enhanced DTS can assess the working situations of equipment including efficiency, energy consumption and health situation. Then, AI-enhanced DTS establishes the evaluation model that considers both features of status parameters and historical equipment maintenance. The evaluation model assigns weights to status parameters so as to comprehensively consider the influence of different parameters. The evaluation of DTS considers production efficiency, production quality and energy consumption. Neural network calculates predictive values of assessment indexes. Based on the predictive values, AI-enhanced DTS calculates the overall evaluation by assigning different weights to the three indicators.

4.2. Control strategy

According to the overall evaluation of the physical shop-floor, AI-enhanced DTS makes the optimal control strategy to adjust manufacturing process considering current production states and production targets. Control strategy considers situations and productivities of both equipment and workers, so that it can dynamically adjust production tasks. According to the characteristics of manufacturing tasks, the physical shop-floor has different quantities of human-machine collaboration manufacturing units. The efficiency of human-machine collaboration manufacturing units depends on the efficiency of both machines and workers. AI-enhanced DTS calculates the productivities of equipment, workers and collaborative units according to the analysis of latest production data. Based on the information, AI-enhanced DTS generates the proper control strategy to assign tasks to different units. According to the assigned tasks, machines in specific collaborative units are motivated by the control strategy to cooperate with the corresponding workers.

The goal of the control strategy is to complete manufacturing tasks with high efficiency and low consumption. Control objectives include productivity, production quality, completion time and energy consumption. AI-enhanced DTS utilizes genetic algorithm to solve multi-objective control problem. AI-enhanced DTS simulates the control strategy in the virtual space and evaluates the results before executing it. If the control strategy fails to effectively improve the production process or causes safety problems, AI-enhanced DTS would generate a new control strategy.

When the unexpected events occur such as sudden equipment damage in the physical shop-floor, AI-enhanced DTS can perceive the abnormal state in time according to the collected real-time data. After sensing the emergencies, AI-enhanced DTS adjusts the control strategy and displays the serious emergencies in the service system, so that workers can find out the cause of abnormality in time.

4.3. Interaction consistency.

To realize synchronization between the physical responses and control commands, AI-enhanced DTS applies neural network to solve interaction delay problem. There are mainly two reasons causing interaction delay, namely, perception delay and control delay. The interaction consistency method to solve the delay problem is as shown in Fig.2.

In terms of the perception delay, AI-enhanced DTS obtains the specific delay time of state perception by calculating the delay time of data acquisition, data transmission, and state evaluation. AI-enhanced DTS uses the neural network to build the prediction model, which can calculate the predictive values considering the delay time. AI-enhanced DTS trains the prediction model with collected historical data. The prediction model calculates the predictive values considering the delay time based on the real-time data collected from the physical shop-floor. Meanwhile, the collected data is used to verify the model output and correct the model parameters. Then, AI-enhanced DTS makes the control strategy based on the predictive time, which ensures the accuracy of state evaluation. To solve the control delay, similarly, AI-enhanced DTS calculates the specific delay time of control process that includes control instruction generation time, data transmission time and control execution time. Subsequently, AI-enhanced DTS generates predictive values considering the delay time, and then generates the control strategy based on the predictive data. Therefore, AI-enhanced DTS calculates predictive values and makes the corresponding control strategy to realize interaction consistency.

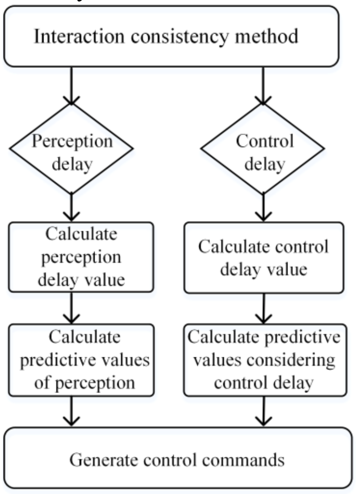

Fig. 2. Interaction consistency method

In conclusion, AI contributes to solve the interaction problems in DTS. AI enhances DTS to evaluate the overall states of the physical shop-floor and generates control strategies. Moreover, through making predictive values, AI ensures physical-virtual synchronization between state perception and control execution.

5. Enabling technologies for interaction in DTS

Interaction in DTS not only contains the connection between the physical and virtual spaces, but also emphasizes the physical-virtual synchronization. Therefore, the enabling technologies can be summarized by three aspects, namely, perception, control and interaction consistency, as shown in Fig.3.

To perceive the state of the physical shop-floor, DTS acquires physical data and recognizes physical objects. Therefore, sensing technology, detection technology, tracking technique and automatic identification are necessary for DTS [8]. Since DTS requires to evaluate the overall state of the physical shop-floor before optimizing the production process, state assessment technology is also crucial. Through analyzing the physical situations as well as production tasks, DTS makes the optimal control strategy to adjust production. Hence, it is particularly important for DTS to combine management technology, optimization technology, multi-agent cooperative control and human-machine collaborative control technology [8]. In addition, DTS needs to consider security problems when making control decisions. For interaction consistency, DTS realizes physical-virtual synchronization, which requires interface, communication technology, virtual-actual fusion, and physical-virtual synchronization technology [8]. Moreover, DTS combines model iteration technology to adjusts model parameters in real time to promise model accuracy.

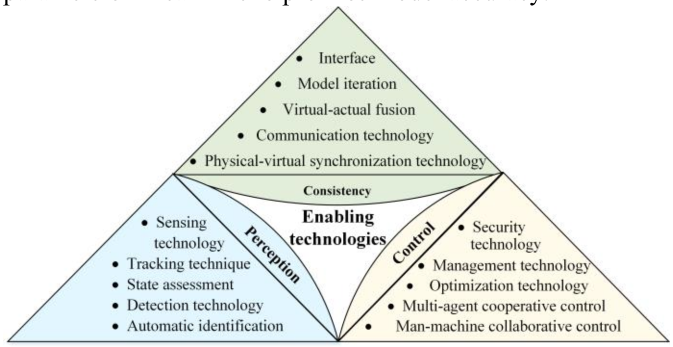

Fig. 3 Enabling technologies for interaction in DTS

6. Conclusion and future work

DTS, as a typical application of DT, has received extensive attention. However, how to achieve effective interaction remains an important issue in DTS. AI has been widely used to solve manufacturing problems, which has great potential to handle the issues. In this paper, existing interaction issues in DTS are analyzed from state perception, control strategy and interaction consistency. Then, a framework of AI-enhanced interaction in DTS is proposed and the implementation mechanism is introduced. Combined with AI, DTS accurately evaluates the overall situation of the physical shop-floor and generates control strategies. AI-enhanced DTS provides an effective method to ensure synchronization between state perception and control execution. Moreover, enabling technologies for interaction in DTS is introduced from the above three aspects.

It is worth mentioning that there are some limitations to the current work. This article focuses on the combination of AI to enhance DTS. However, at present, as the internal logic of the neural network behavior is ambiguous, the reliability of generated data by neural network still needs further study. In addition, the robustness of the control system in AI-enhanced DTS is also an issue that needs more attention. The future work will focus on the following aspect: (1) DT applications in specific manufacturing scenes based on AI, (2) specific evaluation methods in AI-enhanced DTS, and (3) control issues and interaction methods in AI-enhanced DTS.

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