JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 37, 93-105 (2021)
DOI: 10.6688/JISE.202101_37(1).0007

Dynamic Production Scheduling of Digital Twin Job-Shop Based on Edge Computing*

LI-ZHANG XU+ AND QING-SHENG XIE
Key Laboratory of Advanced Manufacturing Technology
Guizhou University
Guiyang, 550025 P.R. China
E-mail: waterprint2018@163.com

The current production scheduling models cannot effectively enable the real-time interaction between information space and physical space. To dynamically schedule twin digital job-shop, this paper attempts to realize the dynamic scheduling of digital twin job-shop (DTJ) based on edge computing. First, the architecture of the DTJ was established by adding the digital twin between the business management layer and the operation execution layer of the traditional job-shop. On this basis, the DTJ was fully modelled, and the manufacturing process was monitored, analyzed and managed remoted by edge computing. To realize dynamic scheduling, a DTJ scheduling model was established through data mining. The model consists of two parts: a data collection model and a multi-scheduling knowledge model. Finally, the proposed DTJ scheduling model was verified through simulation on an actual job-shop. The research results shed new light on the optimization of manufacturing process in various types of job-shops.

Keywords: digital twin, edge computing, job-shop scheduling, manufacturing process, data mining

1. INTRODUCTION

In traditional job-shops, the manufacturing process mainly includes operation execution, data acquisition/monitoring, production line control and unit control [1]. However, it is extremely difficult to schedule the manufacturing process in a flexible manner, due to the lack of effective simulation tool, job-shop information model, and independent decision-making mechanism. Digital twin technology [2], which can be deeply integrated with the said process, offers a viable solution to intelligent job-shop scheduling.

Digital twin is a simulation technique involving multiple disciplines and scales. This technique fully utilizes physical model, sensor, operation logs and various other data, tracking the entire lifecycle of physical products in virtual space. The integration between digital twin and job-shop scheduling gives birth to a novel concept: digital twin job-shop (DTJ). The DTJ mainly consists of physical job-shop, virtual job-shop, job-shop service system and job-shop twin data [3, 4].

The physical job-shop is a real job-shop that receives production tasks from the job-shop service system, and executes the tasks by the strategy optimized through virtual job-shop simulation. Virtual job-shop, the computer equivalent of physical job-shop, monitors, predicts and optimizes the production activities through simulation. Job-shop service system refers to all software in the job-shop. The system implements digital twin-driven operations, and receives feedbacks of the physical job-shop. The job-shop scheduling

Received March 24, 2020; revised April 25, 2020; accepted May 22, 2020.
Communicated by Mahmoud Abdel-Aty.
* This work was supported by the National Natural Science Foundation of China (Grant No. 61863005).

model is the key component of the job-shop service system.

Traditionally, the manufacturing process of the job-shop is usually scheduled based on cloud computing. During the scheduling, the data need to be transmitted to the cloud computing center for processing. However, cloud computing is not suitable for real-time manufacturing systems, for reasons like the high time consumption in data transmission and processing. This calls for a solution with good real-time performance at a low cost of computing resources.

In this paper, a dynamic DTJ scheduling model was established based on edge computing. Specifically, the DTJ architecture was modelled by adding the digital twin to the traditional job-shop. The DTJ scheduling model was then set up through data mining. Thanks to edge computing, the proposed model can monitor and control the manufacturing process remotely, laying the basis for high-quality, efficient and low-cost job-shop scheduling.

There are two major contributions of this paper: (1) A new knowledge-based scheduling model, driven by digital twins, was developed to make up for the lack of the fusion between information space and physical space in existing scheduling models; (2) Based on random forest, a scheduling rule mining model was established for the dynamic job-shop scheduling problem. On this basis, the scheduling of digital twin job-shop was optimized, using the simulation technology under the concept of digital twin.

2. LITERATURE REVIEW

Digital twin technology was extended by Githens [5] from information mirroring model. Tao *et al.* [6] proposed the concept and reference architecture of the DTJ, and discussed the virtual-physical integration of the DTJ from five dimensions: physical entities, virtual entities, services, twin data, and component connectivity. Sun *et al.* [7] established a series of DTJ models based on physical data, including physical model, ontology-based digital model and simulation model, and identified the relationship between physical and digital models. From the perspective of digital twin, Huang *et al.* [8] explored the production management, control framework and key techniques of aircraft assembly job-shop. Schleich *et al.* [9] studied the realization methods of product digital twin in terms of product design and manufacturing service, and constructed a real-time visual monitoring system for complex product assembly job-shop. Leng *et al.* [10] put forward a four-layer DTJ framework consisting of job-shop management layer, station monitoring layer, operation execution layer and data support layer, and examined the job-shop scheduling under the visual application. Zheng *et al.* [11] collected and processed real-time data to build a digital twin production system, and expounded the feasibility of digital twin in realizing cyber-physical production (CPP) systems. Zhuang *et al.* [12] suggested setting up visual digital twin models by web service and augmented reinforcement (AR). Focusing on cloud-based machine maintenance, Coronado *et al.* [13] relied on the cloud infrastructure in DTJ model to realize the interaction between software services and physical entities. Based on digital twin, Liu *et al.* [14] developed a strategy for lifecycle management and optimization of Industrial Internet of Things (IIoT).

Uncertain disturbances are common to production systems, especially complex production systems like the flexible job-shop. In the event of emergencies (*e.g.* machine failure and human error), sudden disturbances may occur in the job-shop, causing job-shop scheduling to fluctuate. To solve the problem, many scholars have probed deep into the job-shop manufacturing process. Rohaninejad *et al.* [15] designed an intelligent static scheduling method for flexible job-shop, with the aid of the separation graph model. Yahouni *et al.* [16] put forward multiple job-shop scheduling strategies based on artificial immune system (AIS) algorithm. Oyekan *et al.* [17] measured the global impact of disturbance factors, and created the dynamic scheduling strategy for the affected jobs. Xu *et al.* [18] applied digital twin in the manufacturing process of structural parts job-shop. Cao *et al.* [19] reused and evaluated process knowledge with digital twin, and thus reduced the cost and time of the manufacturing process. Lv and Qiao [20] associated the data of operation execution system with the data of machines, and set up a TDJ to optimize the manufacturing process. Zhuang *et al.* [21] combined digital twin, enterprise information system and information technology to design and implement a job-shop management and control system.

3. DTJ ARCHITECTURE

Digital twin provides an effective tool for the interaction and fusion of physical and virtual space [22]. This emerging technique is of great significance to job-shop scheduling. Here, the DTJ architecture (Fig. 1) is established to facilitate the monitoring and control of the manufacturing process.

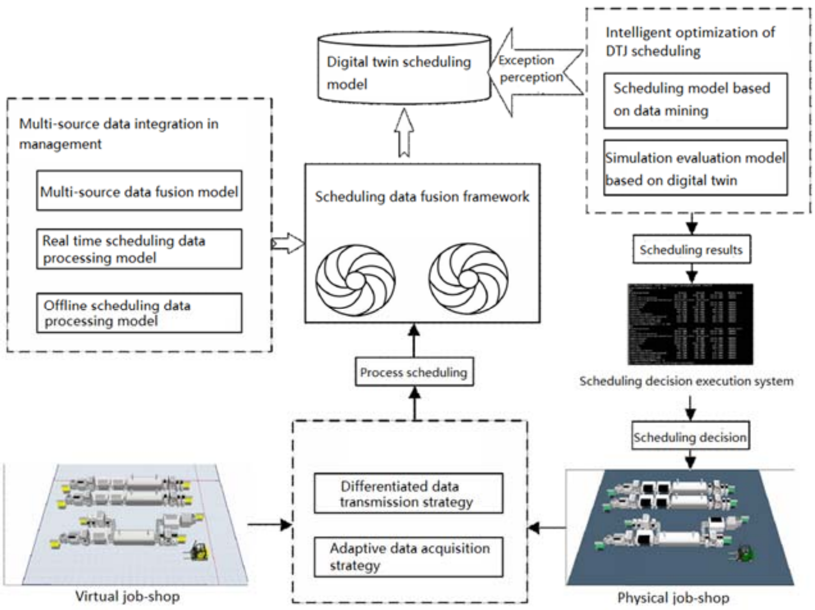


Fig. 1. The architecture of the DTJ.

The physical job-shop is the collection of all physical entities in the real job-shop, while the virtual job-shop is the projection of the physical job-shop in the virtual space. The virtual job-shop contains the elements, data, models and spatial information of the physical job-shop. These components are described by models on three levels: elements, behaviors and rules.

On the element level, the virtual job-shop details the geometry and physical features of production elements (*e.g.* operators, machines, objects and environment) by 3D software and finite-element method.

On the behavior level, the virtual job-shop models the behavior and response mechanism of job-shop elements through 3D simulation, and provides the virtual models of operator behaviors, machine operations and material transportation.

On the rule level, the virtual job-shop constructs models for association rules, job-shop operations and evolution rules through data mining, such that the DTJ operations match the actual situation (behavior, state, operation and evolution) of the physical job-shop.

3.1 Composition of DTJ

As shown in Fig. 2, the DTJ is mainly composed of data exchange interface, simulation analytical model and job-shop information model. The data exchange interface passes any simulation request from the external system to the simulation analytical model, which receives basic data from the job-shop information model. The simulation results are fed back to the external system via the data exchange interface. Both simulation analytical model and job-shop information model are continuously improved by digital twin, which boasts excellent self-learning ability.

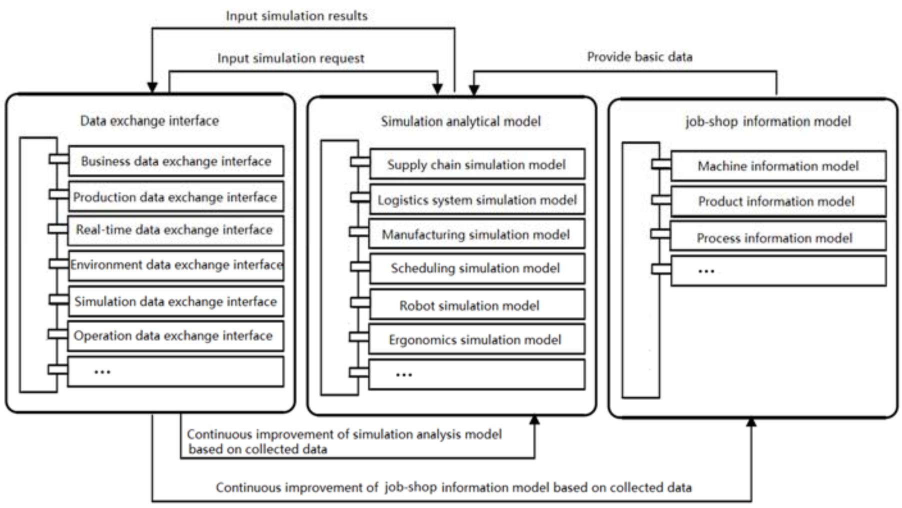


Fig. 2. The composition of DTJ.

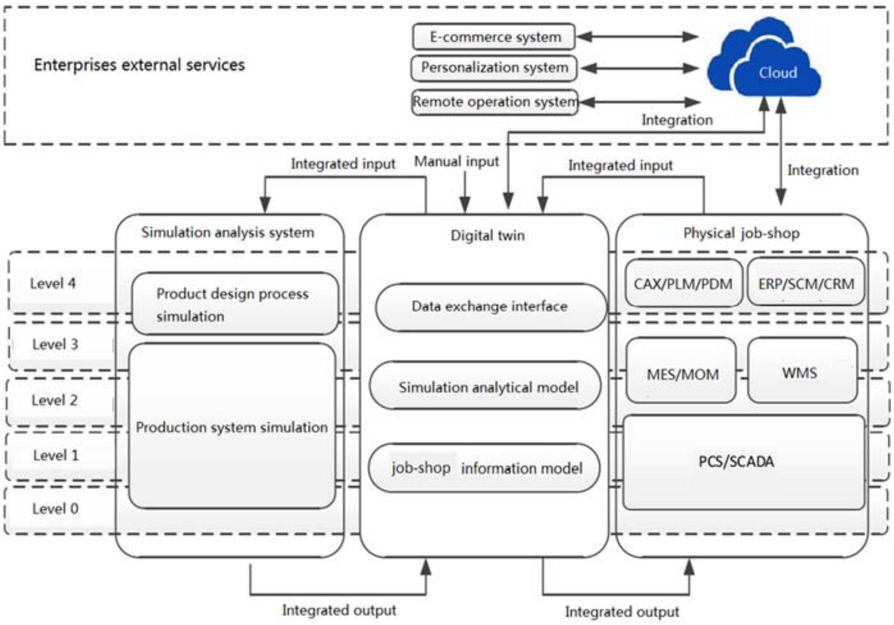
The data exchange interface supports a variety of data exchange modes. It is managed by an extensible data exchange interface adapter. The simulation analytical model enables the digital twin to make analysis and decisions, and exists as the digital twin of the simulation object (*i.e.* defining all the information and behaviors of the object). The job-shop information model provides the basic data of the DTJ and the digital mapping of physical job-shop. In this model, logical expressions are available for dynamic data on production activities and static data on machines and infrastructure.

3.2 Information Integration Architecture

As shown in Fig. 3, the information integration architecture of the DTJ is made up of enterprises external services, physical job-shop, digital twin and simulation analysis system. Among them, simulation analysis system and digital twin are two separated modules that work together through information integration. The simulation analysis system only simulates product design and production system, because this research focuses on the application of digital twin in dynamic job-shop scheduling.

According to the ANSI/ISA-95 standard, manufacturing enterprises are divided into five levels: Level 0 executes the production operations; Level 1 measures and controls the manufacturing process; Level 2 detects, monitors and automatically controls the manufacturing process; Level 3 controls the workflow and process of production; Level 4 prepares the plans for production, material demand, product delivery and shipment.

The manufacturing process of the DTJ spans from Level 0 to Level 2. Based on the demand of information integration, the digital twin covers all five levels of manufacturing enterprises. Product design and production system of the simulation analysis system respectively cover Levels 3-4 and Levels 0-3, respectively.



Note: SCADA: Supervisory control and data acquisition; WMS: Warehouse management system; CAX: Computer-aided X; MOM: Material on machine; PCS: Process control system

Fig. 3. Information integration architecture.

The data collection and feedback mechanism will intervene, if the real-time scheduling data of the physical job-shop deviate from the preset value. On the one hand, the scheduling activities of the two job-shops will be accurately depicted; on the other hand, the scheduling of the two job-shops will be iteratively optimized.

4. DTJ SCHEDULING MODEL

The job-shop scheduling is essential to the management and control of manufacturing process. Once the job-shop is disturbed, the production plan will be immediately affected. Our DTJ scheduling model aims to mine the scheduling knowledge embed in all elements, processes and services, and thus iteratively optimize the scheduling decision.

Intelligent manufacturing directly hinges on the intelligent interaction between physical space and information space. The interaction helps to enhance the autonomy, intelligence, and predictability of scheduling. However, none of the existing schedulers support the real-time interaction between the two spaces. To solve the problem, this paper attempts to design a dynamic scheduling model of digital twin job-shop.

In our model, the real-time scheduling data collected from the physical job-shop are mapped to the corresponding model in virtual job-shop, forming a collaborative optimization network. When the real-time scheduling data deviate from the preset values, the model in virtual job-shop will detect the anomalies, revise the abnormal range, and decide wither to make a response.

Considering the interoperability and scalability of real-time edge computing, a cell-level data twin system must have state awareness, support data computing/processing, and control physical entities. Edge computing adopts an architecture that extends computing, network, and storage functions from cloud to edge. Under this architecture, the data are analyzed in edge nodes, making it possible to perceive, calculate and control objects. Here, the physical devices and network parts of manufacturing resources are fused into a cell-level digital twin system. The system functions include real-time processing of perceived data, data buffering, real-time data control, actuator monitoring, fault diagnosis, extraction of health features, fault processing, and safe shutdown.

If it is necessary to respond to anomalies, the DTJ scheduling model will use the knowledge models provided by edge computing to optimize the results and select the optimal decision-making scheme. The final scheme will be converted into control commands and issued to the physical job-shop through edge computing.

In the physical job-shop, there are lots of data on the edges, and many local application systems. Considering the strong real-time requirements, it is necessary to enhance the ability to execute tasks and analyze data on network edges. Hence, the edge cloud, *i.e.* the small-scale cloud data center on network edge, was adopted to process data and make decisions in real time. The structure of edge computing in the physical job-shop is presented in Fig. 4.

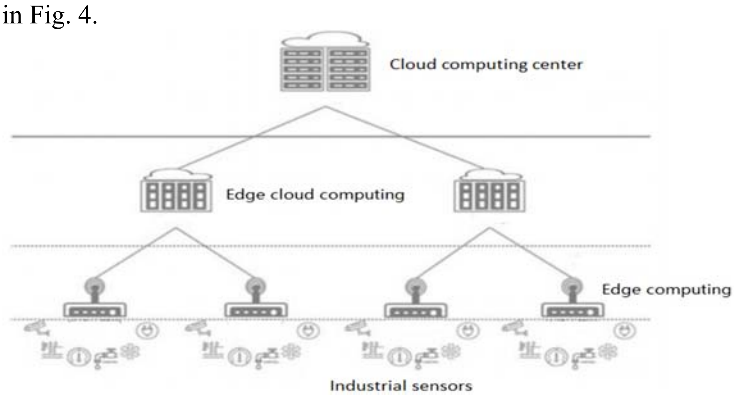


Fig. 4. The structure of edge computing in the physical job-shop.

Data mining and edge computing were introduced to guide job-shop scheduling, aiming to make quick responses to the changing environment. There are many data mining algorithms, such as decision tree (DT) [23] and deep neural network (DNN) [24]. Each algorithm has its unique features. No single algorithm can achieve the best performance in all job-shop scheduling problems (JSPs).

In our DTJ scheduling model, the optimal scheduling schemes are obtained under the guidance of various knowledge models, according to the predicted disturbances and tracked behavior of job-shop elements. In the meantime, the simulation results of each optimal scheduling scheme are converted into training examples for the update of knowledge models.

4.1 Data Collection Model

For DTJ scheduling, it is important to build a scheduling data source, which serves as the sole integration and sharing platform of scheduling data. The scheduling data (Fig. 5) collected from the physical and virtual job-shops were divided into two parts: those for the mining of scheduling rules and those for the application of scheduling rules.

Besides, the collected scheduling dataset D_H was also split into three parts $d1$, $d2$ and $d3$. Among them, $d1$ is the real-time state of scheduling elements, $d2$ is the scheduling process, and $d3$ is the plan of scheduling activities. Because the DTJ scheduling aims to select the suitable machine for each job and eliminate idle machines in disturbed environment.

As shown in Fig. 5, the scheduling dataset contains both offline data and real-time data from physical and virtual job-shops. These data must be collected efficiently and reasonably, such as to speed up the interaction between physical and virtual spaces and the mining of scheduling rules.

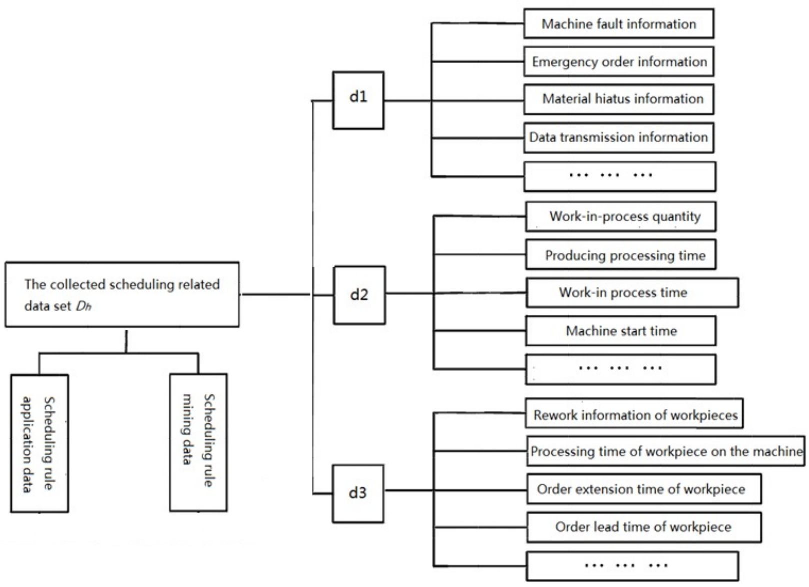


Fig. 5. The scheduling dataset.

This paper adopts an adaptive data acquisition strategy [25], in which the sampling frequency of the sensors is adjusted dynamically by edge computing. The dynamic adjustment was conducted according to the variance between the sensor data in several cycles.

The Bartlett's test [26] was carried out to test whether the datasets collected in several cycles are from the population with equal variances. If the datasets collected by a sensor have the same variance in several cycles, the sampling frequency will be reduced; otherwise, the sampling frequency will be increased.

Suppose a sensor collects T datasets in T cycles. Then, the Bartlett's test for the datasets can be implemented in the following steps:

Step 1: Calculate the following statistics:

$$\chi^2 = \frac{(P-Q)\ln \xi_t^2 - \sum_{q=1}^{Q}(p_q - 1)\ln \xi_q^2}{\lambda} \tag{1}$$

$$P = \sum_{q=1}^{Q} p_q \tag{2}$$

$$\lambda = 1 + \frac{1}{3(Q-1)}\left(\sum_{q=1}^{Q}\left(\frac{1}{p_q - 1}\right) - \frac{1}{p-Q}\right) \tag{3}$$

$$\xi_t^2 = \frac{1}{P-Q}\sum_{q=1}^{Q}\xi_q^2 \tag{4}$$

where P is the total data amount of Q datasets; ξ_t^2 is the population variance of all datasets; p_q is the data volume of the qth dataset; ξ_q^2 is the population variance of the qth dataset.

Step 2: Judge whether the population variances of Q datasets are equal. Compare the calculated statistic χ^2 with the threshold of chi-square distribution $\chi^2_{a(Q\text{-}1)}$, where a is the significance level and $Q-1$ is the degree of freedom. If $\chi^2 > \chi^2_{a(Q\text{-}1)}$, the population variances of Q datasets are significantly different under the significance level of a; if $\chi^2 > \chi^2_{a(Q\text{-}1)}$, the population variances of Q datasets are the same under the significance level of a.

The scheduling dataset D_H contains numerous features of the scheduling environment and an abundance of scheduling knowledge. However, there are also many useless or incorrect rules or patterns. To improve the data quality, this paper constructs a multi-index screening mechanism to process the scheduling dataset. Three indices were selected as the bases for screening, namely, the maximum makespan, the total delay, and the total machine load. The data that satisfy the thresholds for the three indices were inputted to the rule mining algorithm.

4.2 Multi-Scheduling Knowledge Model

The DTJ scheduling model needs to fully utilize the scheduling knowledge from the digital twin data source. Therefore, a multi-scheduling knowledge model was proposed based on digital twin. Three algorithms were selected to mine the scheduling rules, namely, decision tree (DT), random forest (RT) and radial basis function neural network (RBFNN). The three algorithms were integrated by random forest, an algorithm that fuses multiple trees through integrated learning. Random forest trains and predicts samples with multiple decision trees. The output category of the forest depends on the output categories of individual trees. Based on the three algorithms, the mining and utilization of scheduling rules were derived for dynamic DTJ scheduling. The framework of multi-scheduling knowledge model is displayed in Fig. 6.

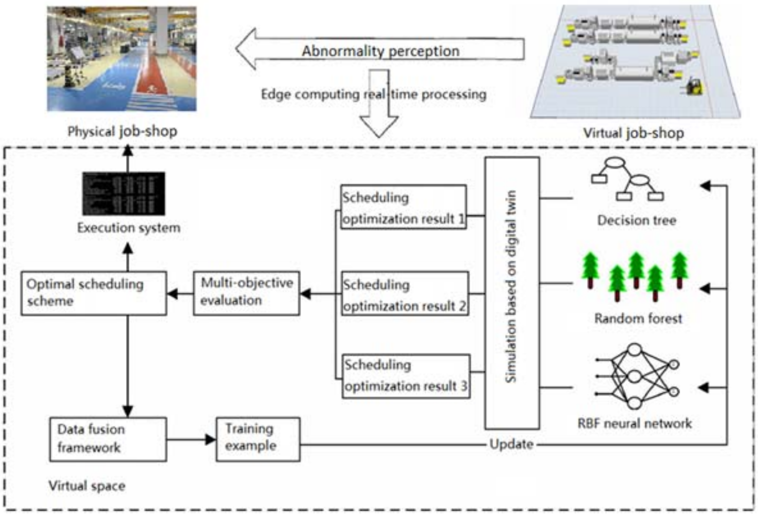


Fig. 6. The framework of multi-scheduling knowledge model.

Once the real-time scheduling data of the physical job-shop deviate from the preset value, the multi-scheduling knowledge model in the virtual job-shop will actively perceive the abnormality, quickly identify the range of the abnormality, and determine the necessity of making any response. If it is necessary to optimize the scheduling, the DT, RF and RFBNN will be called to compute the scheduling optimization results, respectively. Finally, the optimization results will be evaluated, and the final scheduling scheme will be produced. Based on the digital twin, the three types of scheduling knowledge can be effectively integrated, achieving better performance than a single type of scheduling knowledge.

5. SIMULATION AND RESULTS ANALYSIS

To verify its effectiveness, the proposed DTJ model was subjected to contrastive simulation on the software Witness. The simulation analysis system was integrated with digital twin through service bus. The system feeds back the results of simulation analysis to the digital twin, which then issues the production plan and simulation strategy to the operation execution system. In return, the manufacturing execution system continuously feeds back the real-time production data to the digital twin. Based on the data, the digital twin improves the simulation analytical model, and outputs the execution result of the production plan.

Fig. 7 presents the physical production line of operation execution system. It can be seen that the production line consists of a 3D warehouse, a loading robot, an automatic guided vehicle (AGV), an assembly robot, a service robot, *etc*.

Fig. 7. Physical production line of operation execution system.

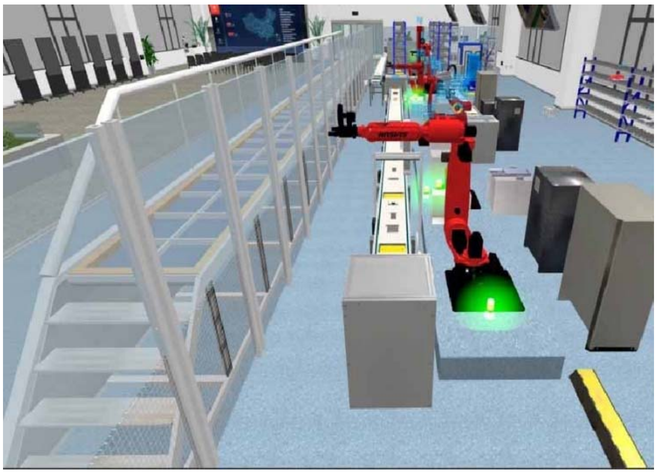


Fig. 8. The DTJ.

Fig. 8 shows the DTJ corresponding to the physical production line. The DTJ mainly includes the production line information model, single machine information model, real-time animation of production line, real-time machine state, job flow information, *etc*.

The simulation object is a flexible job-shop with 7 machines. Eight types of jobs need to be processed in batches (batch size: 10). Each type of jobs has a fixed operation sequence. During the simulation of dynamic DTJ scheduling, the real-time states of jobs and machines were collected. The sampling frequency was initialized as 0.001 per unit time. The scheduling data in the past 60 days were collected and stored in the database, in addition to the information on system disturbance.

Before comparing our model with other scheduling methods, it is necessary to unify the dimensions of all indices, and combined them into a single index. The single performance index can be constructed by:

$$\gamma = 0.5\times\frac{M(rule)-M(best)}{M(worst)-M(best)}+0.3\times\frac{D(rule)-D(best)}{D(worst)-D(best)}+0.2\times\frac{L(rule)-L(best)}{L(worst)-L(best)} \quad (5)$$

where 0.5, 0.3 and 0.2 are the weights of three indicators, respectively; $M(best)$ is the maximum makespan of different scheduling methods; $D(worst)$ is the maximum total delay; $L(best)$ is the maximum total machine load.

The proposed DTJ was compared with DT, RF, RBF and traditional flexible job-shop scheduling algorithm. The performance of each algorithm was measured by maximum makespan, total delay and total machine load. The results of the four contrastive scheduling methods are compared in Table 1.

As shown in Table 1, our model was not as good as other algorithms, as judged by a single index. However, our model, DT, RT and RBFNN all outperformed the traditional flexible job-shop scheduling algorithm in the three evaluation indices. Overall, our model achieved the best scheduling effect among the contrastive methods. In addition, our model exhibited very good real-time performance, owing to the edge computing. Therefore, our model is suitable for actual scheduling environments, which are complex and dynamic.

Table 1. Comparison of different scheduling methods.

Scheduling methods	Evaluation indices		
	Maximum makespan	Total delay	Total machine load
Our model	25.1	1.5	105.6
DT	27.3	8.6	108.2
RT	24.9	6.5	102.3
RBFNN	25.7	8.1	99.8
Traditional flexible job-shop scheduling algorithm	30.6	12.7	96.7

6. CONCLUSIONS

This paper proposes a dynamic DTJ scheduling model capable of intelligent dynamic control of the manufacturing process. The model was constructed with the aid of edge computing, virtual simulation, and data analysis. Simulation results show that our model can approximate the optimal scheduling scheme for multi-objective screening, and outshine the common heuristic scheduling rules. The research results provide important reference for the application of digital twin in the field of job-shop scheduling.

REFERENCES

1. S. Lee, I. Moon, H. Bae, and J. Kim, “Flexible job-shop scheduling problems with 'AND'/'OR' precedence constraints,” *International Journal of Production Research*, Vol. 50, 2012, pp. 1979-2001.
2. Q. Liu, H. Zhang, J Leng, and X. Chen, “Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system,” *International Journal of Production Research*, Vol. 57, 2019, pp. 3903-3919.
3. F. Tao and M. Zhang, “Digital twin shop-floor: A new shop-floor paradigm towards

smart manufacturing," *IEEE Access*, Vol. 5, 2017, pp. 20418-20427.

4. P. Urbina Coronado, R. Lynn, W. Louhichi, M. Parto, E. Wescoat, and T. Kurfess, "Part data integration in the Shop Floor Digital Twin: Mobile and cloud technologies to enable a manufacturing execution system," *Journal of Manufacturing Systems*, Vol. 48, 2018, pp. 25-33.
5. G. Githens, "Product lifecycle management: Driving the next generation of lean thinking by Michael grieves," *Journal of Product Innovation Management*, Vol. 24, 2007, pp. 278-280.
6. F. Tao, *et al.*, "Five-dimension digital twin model and its ten applications," *Computer Integrated Manufacturing Systems*, Vol. 25, 2019, pp. 5-22.
7. Y. Sun, J. Xu, and H. Qiang, "Adaptive neural-fuzzy robust position control scheme for Maglev train systems with experimental verification," *IEEE Transactions on Industrial Electronics*, Vol. 66, 2019, pp. 8589-8599.
8. S. Huang, Y. Guo, Q. Wu, S. Zha, and L. Song, "Optimization algorithm of UWB positioning for aircraft assembly workshop," *Transactions of Nanjing University of Aeronautics & Astronautics*, Vol. 35, 2018, pp. 44-53.
9. B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, "Shaping the digital twin for design and production engineering," *CIRP Annals*, Vol. 66, 2017, pp. 141-144.
10. J. Leng, H. Zhang, D. Yan, Q. Liu, X. Chen, and D. Zhang, "Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop," *Journal of Ambient Intelligence and Humanized Computing*, Vol. 10, 2019, pp. 1155-1166.
11. Y. Zheng, S. Yang, and H. Cheng, "An application framework of digital twin and its case study," *Journal of Ambient Intelligence and Humanized Computing*, Vol. 10, 2019, pp. 1141-1153.
12. C. Zhuang, J. Liu, and H. Xiong, "Digital twin-based smart production management and control framework for the complex product assembly shop-floor," *International Journal of Advanced Manufacturing Technology*, Vol. 96, 2018, pp. 1149-1163.
13. P. D. U. Coronado, R. Lynn, W. Louhichi, M. Parto, E. Wescoat, and T. Kurfess, "Part data integration in the Shop Floor Digital Twin: Mobile and cloud technologies to enable a manufacturing execution system," *Journal of Manufacturing Systems*, Vol. 48, 2018, pp. 25-33.
14. M. Liu, F. R. Yu, and Y. Teng, "Performance optimization for blockchain-enabled industrial internet of things (IIoT) systems: A deep reinforcement learning approach," *IEEE Transactions on Industrial Informatics*, Vol. 15, 2019, pp. 3559-3570.
15. M. Rohaninejad, A. Kheirkhah, P. Fattahi, and B. Vahedi-Nouri. "A hybrid multi-objective genetic algorithm based on the ELECTRE method for a capacitated flexible job shop scheduling problem," *International Journal of Advanced Manufacturing Technology*, Vol. 77, 2015, pp. 51-66.
16. Z. Yahouni, N. Mebarki, and F. Belkadi. "Human-machine cooperation in planning and scheduling: a case study on an unstable environment," *European Journal of Industrial Engineering*, Vol. 12, 2018, pp. 757-780.
17. J. Oyekan, W. Hutabarat, C. Turner, C. Arnoult, and A. Tiwari, "Using Therbligs to embed intelligence in workpieces for digital assistive assembly," *Journal of Ambient Intelligence and Humanized Computing*, 2019, pp. 1-15.
18. A. M. Xu, J. M. Gao, K. Chen, F. M. Chen, and Z. Wang. "Workshop product manufacturing process information integration based on USBOM," *Applied Mechanics*

and Materials, Vol. 607, 2014, pp. 89-94.
19. J. Cao, C. Yin, F. Liu, and Y. Hu. "Descriptive model and general framework of machining workshop digital manufacturing," *Journal of Chongqing University*, Vol. 35, 2012, pp. 8-15.
20. S. Lv and L. Qiao, "A cross-entropy-based approach for the optimization of flexible process planning," *International Journal of Advanced Manufacturing Technology*, Vol. 68, 2013, pp. 2099-2110.
21. C. B. Zhuang, J. H. Liu, H. Xiong, X. Y. Ding, S. L. Liu, and G. Weng, "Connotation, architecture and trends of product digital twin," *Computer Integrated Manufacturing Systems*, Vol. 23, 2017, pp. 753-768.
22. S. Bin and G. Sun, "Optimal energy resources allocation method of wireless sensor networks for intelligent railway systems," *Sensors*, Vol. 20, 2020, p. 482.
23. G. Sun and S. Bin, "A new opinion leaders detecting algorithm in multi-relationship on- line social networks," *Multimedia Tools and Applications*, Vol. 77, 2018, pp. 4295-4307.
24. K. Gorur, M. R. Bozkurt, M. S. Bascil, and F. Temurtas, "GKP signal processing using deep CNN and SVM for tongue-machine interface," *Traitement du Signal*, Vol. 36, 2019, pp. 319-329.
25. B. Ahmadi and O. Simeone, "Two-way communication with adaptive data acquisition," *Transactions on Emerging Telecommunications Technologies*, Vol. 26, 2013.
26. G. Sun and S. Bin, "Router-level internet topology evolution model based on multi-subnet composited complex network model," *Journal of Internet Technology*, Vol. 18, 2017, pp. 1275-1283.

Li-Zhang Xu, Ph.D. candidate in the Key Laboratory of Advanced Manufacturing Technology of Chinese Ministry of Education, is primarily engaged in evolutionary algorithm and intelligent manufacturing. E-mail: waterprint2018@163.com.

Qing-Sheng Xie, born in 1954 in Guizhou, China, is a doctoral tutor, a "national young and middle-aged expert with outstanding contributions", and a member of the Computer Integrated Manufacturing System (CIMS) thematic expert group under the 10th Five-Year Plan. Xie has presided over more than 40 major science and technology projects in China, including the National High-Tech R&D Program (863 Program), the National Natural Science Foundation, the National Science and Technology Project, and the National Development and Reform Commission (NDRC) Project. The main research direction is manufacturing informatization. E-mail: qsxie@gzu.edu.cn.