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FLEXIBLE JOB SHOP SCHEDULING BASED ON DIGITAL TWIN AND IMPROVED BACTERIAL FORAGING

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Abstract
To realize the dynamic scheduling of complex workpiece processing in complex workpiece job shop, a hybrid dynamic scheduling method with Digital Twin and improved bacterial foraging algorithm (IBFOA) is proposed to minimize the maximum completion time and machine load. During the actual workshop processing, the flexible job shop scheduling problem (FJSP) is divided into two sub-problems: machine assignment and process sequencing. The initial scheduling scheme is completed using an IBFOA to construct a Digital Twin flexible job shop scheduling model. Digital Twin model is used to solve the impact of workshop emergencies. Based on typical benchmark cases and real data from a machine company's mould shop, the machining shop production scheduling experiments are conducted. The results show that the scheduling scheme using the IBFOA combined with the Digital Twin can optimize the system performance as a whole and effectively deal with the problem of extended production time caused by disruption. The algorithm can obtain the most satisfactory scheduling solution and the effectiveness of solving the multi-objective FJSP are verified.
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Key Words: Flexible Job Shop Scheduling, Improved Bacteria Foraging Optimization Algorithm, Digital Twin, Complex Product, Dynamic Scheduling

1. INTRODUCTION

FJSP not only considers the order of the processes to be processed, but also allows a process to be selected among multiple machines capable of processing. Moreover, it increases the complexity of problem modelling and calculation [1]. In multi-objective FJSP, disturbance problems such as machine failure, worker turnover and emergency workpiece plug-ins are uncertain, and the emergence of these uncertainties will lead to frequent rescheduling, which not only degrades the scheduling performance, but also may lead to production interruption. Multi-objective FJSP includes two sub-problems: machine allocation and process scheduling. The solution of the problem includes two stages: ① scheduling scheme optimization stage, this stage mainly searches the optimal solution set that meets the conditions, that is, non-dominant solution; ② scheduling scheme decision-making stage, this stage mainly selects the most satisfactory scheduling scheme from the optimal solution set. Lou et al., aimed at the green low-carbon distributed job shop scheduling problem, designed the artificial bee colony model based on Pareto optimization method, and effectively solved the low-carbon distributed FJSP dual-objective optimization problem considering carbon emissions [2]. Li et al. proposed an extended dual-resource constrained FJSP considering equipment personnel. They used multi-team collaborative teaching and learning optimization algorithm to select equipment personnel resources and optimize process scheduling of components, and obtained good results [3]. Ding et al. put forwards a NSGA-II algorithm based on hybrid mutation operator for FJSP with multi-objective constraints. The effectiveness of the optimization ability and computational efficiency of the algorithm was verified by numerical simulation [4]. Poroskun et al. proposed an intelligent optimization algorithm for a class of flexible job shop scheduling problems, and proposed a new improved strategy around the three stages of the artificial bee colony [5]. In order to solve the problem of only optimizing a single target in the existing critical path-based

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domain search, Wang et al. mixed local and global search algorithms and tested the effectiveness of this algorithm through two international case sets [6]. However, the data in the physical space is difficult to feedback to the information space in time, which makes the function of the information space difficult to complete online, which seriously affects the dynamics and predictability of job shop scheduling [7]. How to realize dynamic scheduling through data exchange in workshop physical information space is an urgent problem to be solved in the field of job shop scheduling. Some scholars used fast rendering method of mathematical twin model based on parallel computing framework to solve the problem of fast rendering of digital twin module for large-scale scenes [8]. Liang et al. established the digital twin agent of physical production line based on digital twin technology to complete the design of full-cycle intelligent workshop system from twin construction, multi-step simulation debugging and information exchange [9]. Ning et al. proposed a system-oriented DT framework, which has process correlation and interaction mechanism and integrates multiple models for dynamic process modelling. The data model is built as the core driving model of DT. The results show that the method can be used in multi-functional applications such as cutting parameter optimization, machining related variable visualization and machining stability evaluation [10].

Combining with the advantages of the digital twin [11, 12], which enables interaction between the information space and physical space, and simulates and predicts the physical space, a dynamic scheduling strategy of FJSP is proposed by using the digital twin in FJSP.

2. COMPLEX PRODUCT FJSP SCHEDULING MODEL

2.1 Definition of symbols

N – Number of workpieces
M – Number of machines
i – Workpiece index number
n_i – Work order index number
R_{ij} – Process j of workpiece i
M_{ij} – A collection of machines for the j^{th} process of workpiece i, $M_{ij} \subseteq \{1, 2, \ldots, M\}$
m – Processing machine index number $m \in \{1, 2, \ldots, M_{ij}\}$
S_{ijm} – Workpiece R_{ij} is machined on m
t_{ijm} – Machining time for workpiece R_{ij} on m
b_{ijm} – Start time of process R_{ij} on machine m
C_{ijm} – Completion time of process R_{ij}

2.2 Modelling

The FJSP is modelled as: there are N workpieces to be machined in the workshop with M machines, each workpiece i contains n_i ($n_i \geq 1$) processes and the processes are to be carried out according to a specified machining route. Each process R_{ij} can be processed by any of machine that can handle machine m [13, 14]. Differences in machine performance result in different completion times for process R_{ij} on machine m. The objective is to determine a machine m for each process R_{ij}, as well as to sequence the workpieces on machine m and determine the start time of the process so that the performance indicators are optimal. FJSP contains two sub-problems: (i) the machine allocation sub-problem; (ii) the process scheduling sub-problem.

Among the many factors that affect the efficiency of FJSP scheduling, the control of working hours is the most important influencing factor, and the negative impact of most disturbances is reflected through changes in working hours. Traditional re-scheduling methods often assume that each process has a defined number of processing hours, and the scheduling solution obtained from this may deviate from the actual shop floor scheduling, resulting in frequent re-scheduling of actual production, which affects the efficiency of the shop floor. There are currently two main types of methods for dealing with variations in working hours: one is to set working hours as an uncertain quantity and describe the variation in working hours through fuzzy numbers or random distributions; the other is to use big data analysis techniques to combine historical and real-time data from the shop floor to predict working hours before or during scheduling. However, none of the above methods take into account the impact of the scheduling scheme itself on man-hours. In a discrete assembly plant, the man-hours required for the current process may be influenced by its predecessors due to the relative dispersion of the processes; the transfer time between different stages of the same product, and the changeover time between different products being processed on the same machine may change depending on the scheduling scheme, thus affecting man-hours. The digital twin-based shop floor scheduling framework consists of four main components. Centred on shop floor twin data, the physical shop floor production execution system provides real-time access to information related to scheduling in shop floor production. The virtual workshop triggers the update and optimization process based on the real-time sensed scheduling data, combined with historical scheduling, and at the same time uploads the simulation data generated during the update process to the workshop twin data centre. The fused twin data can drive different workshop services such as production information statistics, shop floor status monitoring, and online prediction of working hours. The output of the services is executed through the workshop twin data centre, forming a workshop scheduling process with continuous iterative evolution of reality and fiction. With this new shop floor scheduling framework, it is possible to obtain all the data needed for production scheduling accurately, as well as to analyse shop floor status and predict assembly man-hours based on twin data, and to adjust scheduling solutions through constant interaction and feedback between reality and reality, thus managing disruptions.

2.3 Target function

The primary goal of efficiency in a production company is to complete production in a timely and efficient manner, this paper assumes that the number of workpieces at the initial moment is N, and that each workpiece has multiple processes and M optional machining machines. The symbols m, i, i', j correspond to the machine, the initial workpiece, the newly added workpiece, and the number of the process on the workpiece. R_{ij} denotes the j^{th} process of the workpiece W_i and the time required for machining process R_{ij} on machine m is denoted as $t_{ijm}(t'_{ijm})$.

(1) Minimize maximum completion time $f1$

$$\begin{gathered} f1 = \min(F) = \min[\max(\sum_{m=1}^{M} F_m)] \\ F_m = \sum_{i=1}^{N} \sum_{j=1}^{n_i} (S_{ijm} b_{ijm} + S_{ijm} t_{ijm}) \end{gathered} \tag{1}$$

In Eq. (1), F presents the completion time, F_m presents the full time on machine m, b_{ijm} presents the begin time for R_{ij} on m.

$$S_{ijm} = \begin{cases} 1, \text{Workpiece } R_{ij} \text{ machining on machine m;} \\ 0, \text{Workpiece } R_{ij} \text{ not machined on machine } m. \end{cases}$$

$$S_{ij'm} = \begin{cases} 1, \text{Workpiece } R_{ij'} \text{ machining on machine } m; \\ 0, \text{Workpiece } R_{ij'} \text{ not machined on machine } m. \end{cases}$$

b_{ij} – Begin time for j^{th} process of the initial workpiece i

$b_{i'j}$ – Begin time for j^{th} process of the new workpiece i'

(2) Minimize the total machine load number $f2$

$$f2 = \min(\sum_{i=1}^{N}\sum_{j=1}^{N_i}\sum_{m=1}^{M} t_{ijm}S_{ijm}) \tag{2}$$

(3) Minimize the maximum number of loads on a single machine $f3$

$$f3 = \min[\max \sum_{i=1}^{N}\sum_{j=1}^{N_i} t_{ikm}S_{ijm}]$$
$$m = 1, 2, \ldots, M \tag{3}$$

3. BASED ON REAL-TIME DATA AND WORKING HOURS ONLINE NEURAL NETWORK PREDICTION

3.1 The improved BFOA

General application of fixed step length in BFOA strategies for problem solving, which limits the convergence of the algorithm [15].

(1) Initialization operation

The location P_o, population size *SP*, chemotaxis times *Nc*, reproduction times N_r and dispersion times *Nd* of individual bacteria were determined.

(2) Chemotactic operation

① Generate unit vector, carry out the turnover and swimming of bacterial individuals, the position of the i^{th} bacterial individual is updated according to the following formula [16]:

$$\theta^i(k+1, j, l) = \theta^i(k, j, l) + cs(i)\varphi(i) \tag{4}$$

$$\varphi(i) = \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{5}$$

In Eq. (4), $\theta^i(k, j, l)$ indicates the i^{th} bacterial individual in the k^{th} chemotaxis, j^{th} replication and l^{th} dispersion.

$cs(i)$ indicates chemotactic step size; $\varphi(i)$ represents direction vector unit length; $\Delta(i)$ represents the generated random vector.

The adjustable step adjustment formula is:

$$cs(i) = mf[\frac{\delta(\delta+1)}{\delta + crowd} - \delta]Bl \tag{6}$$

In Eq. (6), *mf* represents the step adjustment factor, *crowd* represents the crowding distance, $crowd = (nc/SP)$, *Bl* represents the length of the search interval. If *crowd* is small, the bacterial individual is optimized in a larger step; otherwise, the optimization is carried out in smaller steps.

② Differential variation

Using the symbol X_{gb} to represent the global optimal position and X_{lb} to represent the current optimal position, the mutation operator λ is described as follow:

$$\lambda = X_{n1} + \alpha(X_{gb} - X_{n2}) + rad(X_{lb} - X_{n3}) \tag{7}$$

In Eq. (7), $\alpha \in [0.5, 1]$ represent the scaling operator, $rad \in [0, 1]$ represent a random number, $X_{n1} - X_{n3}$ represent a random selection of different bacterial individuals

③ Differential crossover and selection

Cross operation was carried out among the parent individuals, and the test individuals were obtained as follows:

$$V_i = \begin{cases} \lambda_i, \text{if } rad < \beta \text{ or } i = irad \\ X_i, \text{otherwise} \end{cases}$$

β represents crossover operator, *irad* represents a random dimension.

Offspring selection is based on Pareto non dominated sorting [16] and crowding distance.

3.2 Establishment of man hour online prediction model

Forecasting working hours plays a very important role in improving the efficiency of job shop scheduling. The research on the influencing factors of working time in assembly process is divided into the following categories: physical properties of assembly objects, assembly processes, assembly machines and personnel factors. However, at present, the impact of scheduling scheme is less considered in the prediction of working time. This paper presents a real-time working time prediction based on digital twin. The input data includes the operation information of the current operation, the current scheduling plan information, the history and real-time status information of workshop machines. After pre-processing these data, the prediction results are output through the prediction model, and the actual working time cases obtained under common disturbance types are used as training samples to update the model. The purpose of data pre-processing is to transform the original input data into vectors that can be input by the prediction model. In this paper, the type (plates, frames, beams, rods, standard parts and other types) and quantity of assembly objects are used to represent the physical properties of assembly objects, $AO = [O_1, O_2, \ldots, O_i]$, where O_i represents the number of assembly objects of type i. The characteristics of assembly action are characterized by the types and subtypes (picking, positioning, clamping, connecting, locking, sealing and cleaning) of assembly action, $AA = [A_1, A_2, \ldots, A_j]$. where A_j represents the number of operations of the j^{th} assembly action. The characteristics of accuracy requirements are characterized by the types (weight, distance, torque, parallelism, flatness and position) and grades (high, medium and low) of accuracy requirements, $AP = [P_1, P_2, \ldots, P_k]$, where P_k represents the accuracy level of class k progress requirements. Through the current process, the state parameters (static and dynamic) of the machine are used to characterize the characteristics of the machine and tooling, $AD = [D_{n1}, D_{n2}, \ldots, D_{ns}]$, where D_{ns} represents the s^{th} state parameter of the machine numbered n. This study takes into account the impact of the current scheduling scheme on the working time, and it is characterized by the two-level encoding of the current scheduling scheme.

The vector generated after pre-processing is input into the neural network prediction model for prediction. The parameter optimization method used in the model training process is Adam algorithm, the loss function of model training is root mean square error, the activation function of model hidden layer uses Relu activation function which can avoid gradient dispersion, and the output layer uses linear activation function. In the training process, L_2 regularization is used to improve the generalization ability of the model. In the training process, 90 % of the total sample data is taken as the training sample, and 10 % is used to verify the fitting accuracy of the model. Fig. 1 shows the results of the trained model running on the test data set. The results show that the average error rate of the model in the initial test sample is within 10 %.

It can be seen from the results in Fig. 1 that the average error rate of the current model prediction is less than 10 %, which is far lower than the error rate of manual experience test, and the accuracy is improved.

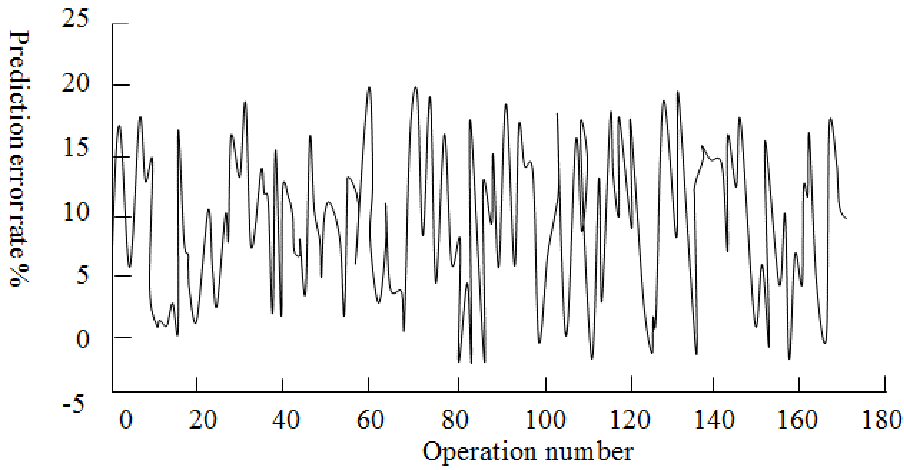

Figure 1: Error rate curve of the model on the test set.

4. DIGITAL TWIN FJSP SCHEDULING FOR COMPLEX PRODUCTS

The proposed digital twin FJSP dynamic scheduling for complex products uses real-time shop floor data and historical data to drive related services for dynamic scheduling of the assembly process on the shop floor. Before assembly, a real-time scheduling solution is used as the current solution for execution. During the execution of the current plan, the shop floor status monitoring service is called to determine whether there is a disturbance event, and if there is an abnormal disturbance, the actual scheduling plan currently being executed is first updated according to the disturbance, and then a real-time scheduling plan is generated and compared with the plan currently being executed to determine whether it needs to be rescheduled; if there is no disturbance, the current plan continues to be executed. If rescheduling is required, the current scheduling scheme is updated to a real-time scheduling scheme, otherwise, the current scheme continues to be executed until all assembly tasks are completed. Through researching actual production workshops, this paper divides disturbance events into three categories: process constraint change, workshop resource constraint change, and time error of assembly execution, where disturbance events involving process constraint change include early completion, emergency order insertion, temporary task cancellation, etc.; disturbance events involving workshop resource constraint change include machine failure, lack of work material, etc.; disturbance events involving time error of assembly execution include work material distribution delay, execution time error, quality problem exclusion, etc.

In the presence of a disturbance event, the real-time scheduling solution generation algorithm and the update process of the actual scheduling solution in the presence of the disturbance generate the corresponding optimized and actual scheduling solutions for the current conditions, respectively. The re-scheduling judgment method is described as follows: firstly, it detects whether the actual scheduling solution generated after the current disturbance meets the constraints, and if it does, it determines whether $|C_1-C_2|>T_{max}$, C_1 indicates the maximum completion time of the optimized scheduling solution under the current conditions, C_2 indicates the maximum completion time of the actual scheduling solution, T_{max} indicates the set reference threshold; if it is not met a re-scheduling is triggered directly and automatically.

5. CASE ANALYSIS

5.1 IBFOA for FJSP

This paper aims to minimize the average completion time f_1, the total machine load f_2 and the maximum load of a single machine, four scale standard problems of classical Brandimarte

(4 workpieces × 5 machines, 8 workpieces × 8 machines, 10 workpieces × 7 machines, 10 workpieces × 10 machines) are solved by IBFOA, and compared with basic bacterial optimization algorithm (BFOA) [17], hybrid bee colony algorithm (HBCA) [18] and IBFOA. It can be seen from Table I that IBFOA can obtain more non-dominant solutions and the optimal solutions in the calculation examples. Taking the 10 × 8 problem as an example, although both HBCA and IBFOA obtain three non-dominant solutions, the solution of HBCA (11, 60, 10) is dominated by the solution of IBFOA (11, 59, 10), the solution of HBCA (10, 62, 11) is dominated by the solution of IBFOA (10, 61, 10) and (10, 59, 11), and the solution of HBCA (11, 59, 11) is dominated by the solution of IBFOA (11, 59, 10) and (10, 59, 11). This shows that IBFOA algorithm has some advantages in performance compared with similar algorithms.

Table I: Results of Kacem examples of different algorithms.

Workpiece × Machine	Objective	BFOA		HBCA			IBFOA			
		***So*₁**	***So*₂**	***So*₁**	***So*₂**	***So*₃**	***So*₁**	***So*₂**	***So*₃**	***So*₄**
4×5	T_x	11		11	12	13	11	11	12	11
	M_t	31		31	31	32	31	30	31	31
	M_x	9		10	8	7	9	8	8	8
8×8	T_x	15	15	14	15	15	14	15	14	14
	M_t	76	75	76	75	73	75	75	73	74
	M_x	12	12	12	12	13	12	12	12	11
10×8	T_x			11	10	11	11	10	10	
	M_t			60	62	59	59	61	59	
	M_x			10	11	11	10	10	11	
10×10	T_x	7		7	6	7	7	6	7	6
	M_t	43		41	42	41	41	42	41	41
	M_x	6		6	5	5	6	5	5	6

In Table I, So_n ($n = 1, 2, 3, 4$) are the solutions, T_x is the maximum completion time, M_t is the total machine load, and M_x is the maximum load of a single machine.

5.2 Dynamic scheduling problem of discrete assembly workshop based on Digital Twin

To verify the effect of using digital twin for FJSP of discrete assembly workshop, the simulation software Flexsim [19-22] was used to simulate the production process of the mould workshop of a machinery company, as shown in Fig. 2.

The Gantt chart of using IBFOA is shown in Fig. 3. The black box indicates that the machine is in the processing state, the white indicates that the machine is in idle state, and the maximum completion time is 726 min. Compared with no optimal scheduling scheme, the production efficiency is greatly improved.

The optimal scheduling solution solved by IBFOA algorithm is put into the simulation model for testing. The input variable of the simulation model is the schedule of the starting processing time of each workpiece. When the scheme is verified by digital twinning, the scheduling algorithm machine utilization is compared with the ideal machine utilization in the actual situation. If the utilization rate is lower in the virtual workshop, rescheduling service is used in the workshop service system to modify the scheduling scheme to improve the utilization rate of real workshop machines.

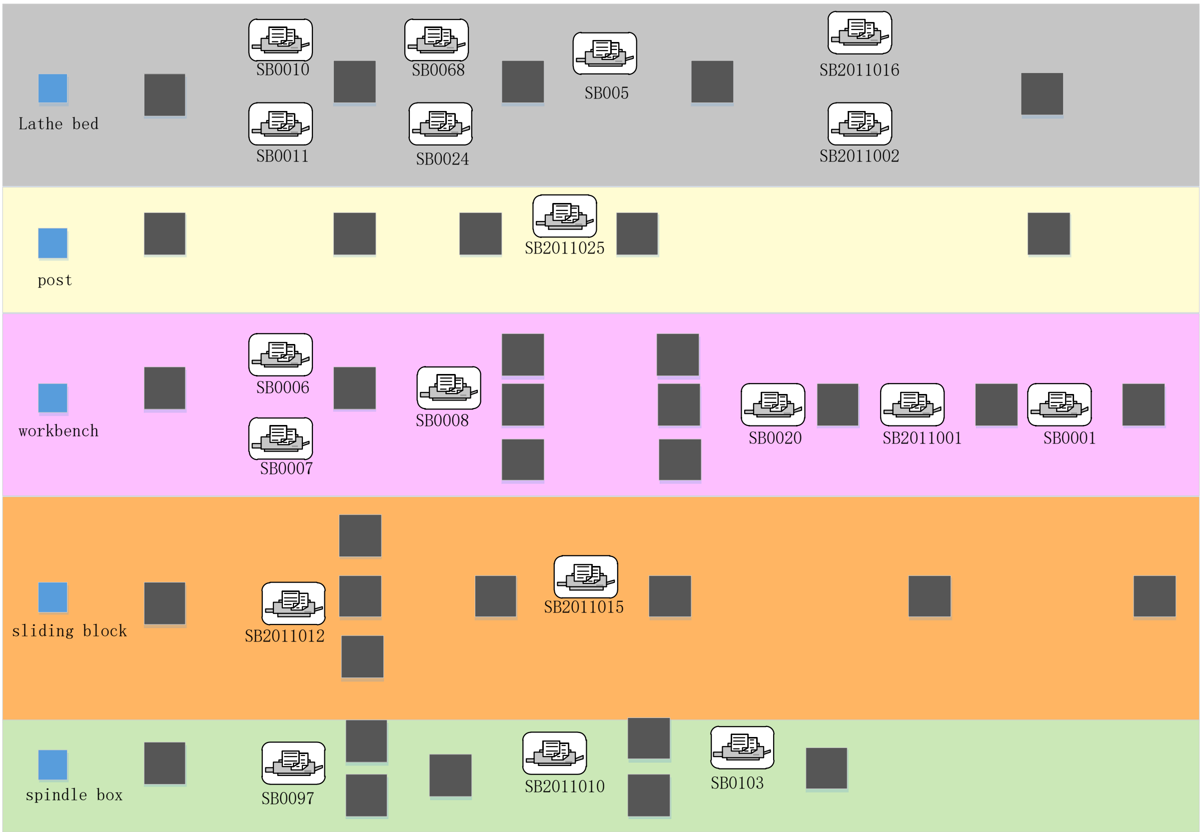

Figure 2: Production process in the virtual workshop.

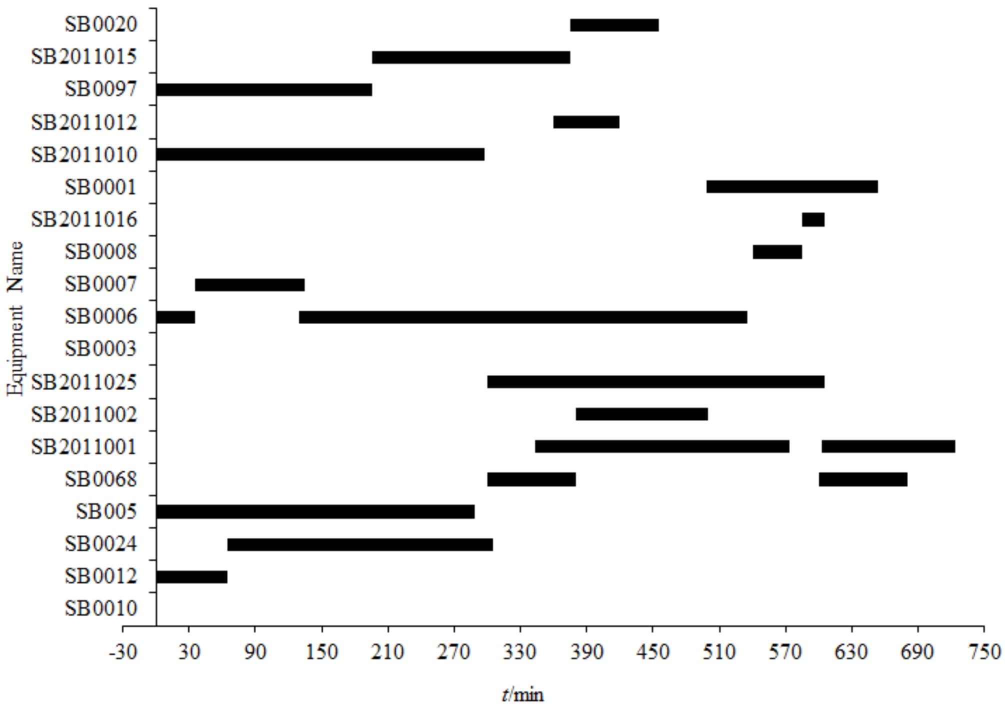

Figure 3: Gantt chart of the production.

Table II: Comparison of machine utilization ratio.

Method	**Makespan** [min]	**Utilization ratio of machine** [%]
Without digital twin	726	88.6
With digital twin	726	100.0

It can be seen from Table II that, the scheduling scheme generated by IBFOA algorithm is verified in advance by digital twinning before production, which can improve the machine utilization rate of the generation system and optimize the performance of the production system in the actual workshop scenario.

5.3 IBFOA algorithm for digital twin to solve FJSP problem

In scheduling without digital twin, if a machining machine fails, the fault will be discovered only when the machine runs for longer than the maximum time originally obtained in scheduling. This type of interference management may lead to too long processing time, resulting in delayed delivery of the workpiece. When digital twin is introduced, as the data in physical workshop and virtual workshop can interact in real time, problems in production can be found in time, and the future production process can be quickly predicted. If the predicted results are beyond the acceptable range, the unprocessed process can be immediately rescheduled.

To verify the effect of digital twin on FJSP, the simulation software is used to generate random disturbances in the production process to simulate emergencies in the production process, as shown in Fig. 4. The processing machine SB2011001 failed at the 505th minute, resulting in an additional 63 minutes of production time, as indicated by the slash shadow.

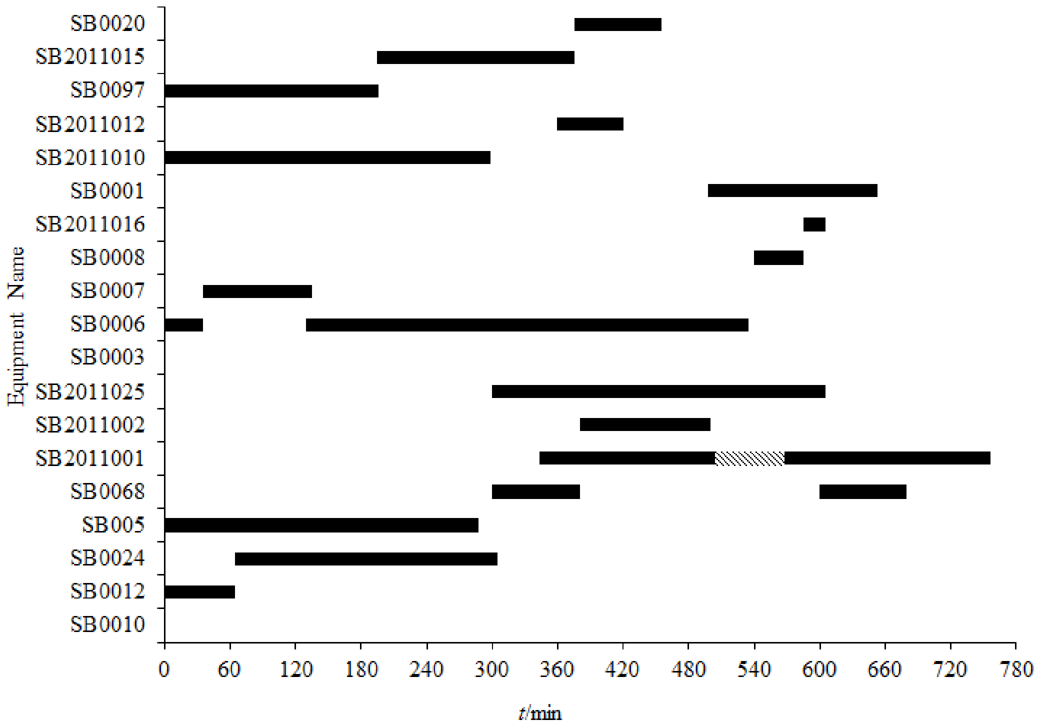

Figure 4: Gantt chart without Digital twin.

In Fig. 4 without the digital twin scheduling strategy, machine failures could not be detected until after production was completed, resulting in longer processing time for subsequent processes and a total production completion time of 759 min, which affected the normal delivery of parts. When using the digital twin, the machine data and production data on the shop floor can be monitored in real time by the sensors installed on the processing machines, and the machine failure time can be predicted in advance, so that the unprocessed processes can be flexibly rescheduled in time, and the affected workpieces can be arranged to other free machines with processing capacity, thus reducing the impact on the total completion time. The total completion time is 726 min, ensuring the timely delivery of production pieces, as shown in Fig. 5. The use of digital twin can both improve machine utilization and reduce production delays.

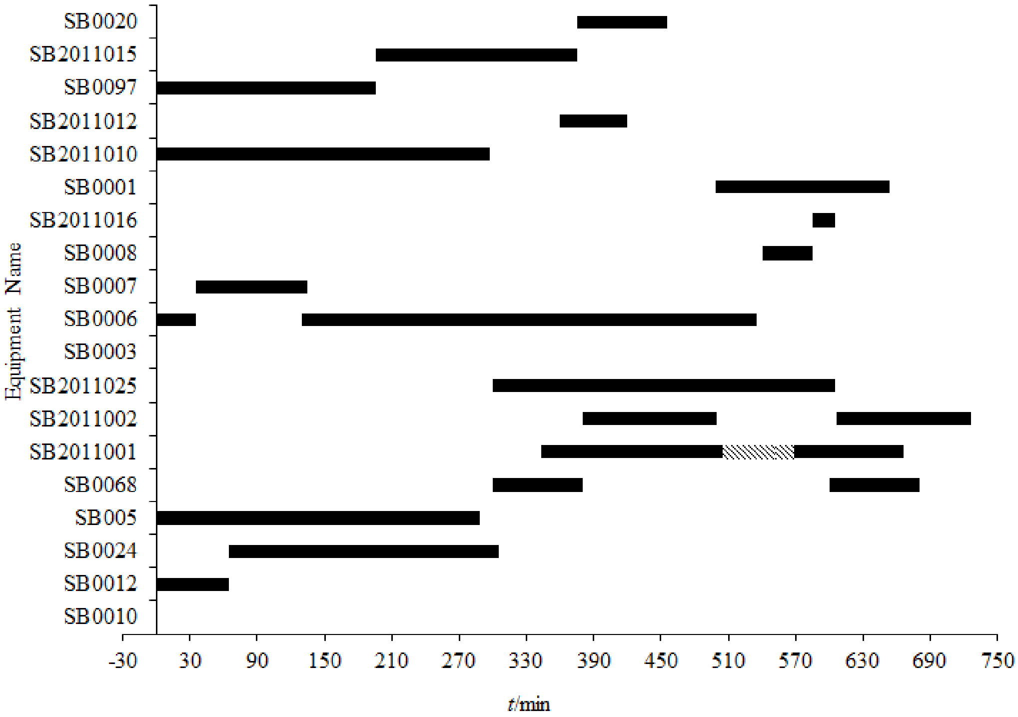

Figure 5: Gantt chart with Digital twin.

6. CONCLUSION

Digital twin and IBFOA for FJSP are studied in this paper, and the online prediction of work hours is carried out based on real-time data and neural network. Combined with the predicted time, the rescheduling of digital twin shop for complex products is realized. Finally, the following conclusions are obtained through case analysis:

(1) This paper takes the actual assembly scheduling in the mould assembly shop of a machinery company as a case study, schedules it by the proposed IBFOA method based on digital twin, and compares the scheduling scheme with that without digital twin technology.

(2) This paper verifies the feasibility and effectiveness of IBFOA with digital twin. The digital twin shop scheduling framework built through physical shop, shop service, virtual shop and data interaction among the three can well realize dynamic and accurate shop production scheduling, thus providing a new idea to realize dynamic shop scheduling with advanced and proactive nature.

The follow-up work will further improve and optimize the theoretical framework of the digital twin-based flexible job shop scheduling for complex products, mainly focusing on the following aspects: (1) combining deep learning algorithms and intelligent optimization algorithms to study the multi-objective dynamic scheduling problem; (2) building and improving the digital twin shop scheduling system based on the actual shop floor.

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REFERENCES

[1] Ning, T.; Wang, Z.; Duan, X.; Liu, X. (2021). Research on flexible job shop scheduling with low-carbon technology based on quantum bacterial foraging optimization, *International Journal of Low-Carbon Technologies*, Vol. 16, No. 3, 761-769, doi:10.1093/ijlct/ctab005

[2] Lou, H.; Zhang, J.; Zhao, Y. (2020). Scheduling method for aerospace components production shop based on extended dual resource constrains, *Computer Integrated Manufacturing Systems*, Vol. 26, No. 12, 3330-3340

[3] Li, J.-Q.; Du, Y.; Tian, J.; Duan, P.-Y.; Pan, Q.-K. (2021). An artificial bee colony algorithm for flexible job shop scheduling with transportation resource constraints, *ACTA Electronica Sinica*, Vol. 49, No. 2, 324-330, doi:10.12263/DZXB.20200382

[4] Ding, Y.; Wang, Y.; Ji, Z. (2020). Collaborative optimization of production and energy consumption in flexible workshop, *Journal of System Simulation*, Vol. 32, No. 12, 2426-2437, doi:10.16182/j.issn1004731x.joss.20-FZ0456

[5] Poroskun, I.; Rothleitner, C.; Heißelmann, D. (2022). Structure of digital metrological twins as software for uncertainty estimation, *Journal of Sensors and Sensor Systems*, Vol. 11, No. 1, 75-82, doi:10.5194/jsss-11-75-2022

[6] Wang, J. H.; Li, Y.; Liu, Z.; Liu, J. (2021). Evolutionary algorithm with precise neighborhood structure for flexible workshop scheduling, *Journal of Tongji University (Natural Science)*, Vol. 49, No. 3, 440-448

[7] Dabner, N. (2012). 'Breaking Ground' in the use of social media: A case study of a university earthquake response to inform educational design with Facebook, *The Internet and Higher Education*, Vol. 15, No. 1, 69-78, doi:10.1016/j.iheduc.2011.06.001

[8] Xiao, Q.; Fang, J.; Wang, L.; Li, J.; Liu, D. (2021). Full cycle intelligent workshop system based on digital twin, *Modular Machine Tool & Automatic Manufacturing Technique*, Vol. 2021, No. 10, 129-132, doi:10.13462/j.cnki.mmtamt.2021.10.029

[9] Liang, Z.; Wang, S.; Peng, Y.; Mao, X.; Yuan, X.; Yang, A.; Yin, L. (2022). The process correlation interaction construction of Digital Twin for dynamic characteristics of machine tool structures with multi-dimensional variables, *Journal of Manufacturing Systems*, Vol. 63, 78-94, doi:10.1016/j.jmsy.2022.03.002

[10] Ning, T.; Wang, Z.; Zhang, P.; Gou, T. (2020). Integrated optimization of disruption management and scheduling for reducing carbon emission in manufacturing, *Journal of Cleaner Production*, Vol. 263, Paper 121449, 8 pages, doi:10.1016/j.jclepro.2020.121449

[11] El Mettiti, A.; Oumsis, M. (2022). A survey on 6G networks: vision, requirements, architecture, technologies and challenges, *Ingénierie des Systèmes d'Information*, Vol. 27, No. 1, 1-10, doi:10.18280/isi.270101

[12] Tao, N.; Shishasha, S.; Peng, Z.; Tao, G. (2021). Disruption management decision model for VRPSDP under changes of customer distribution demand, *Journal of Ambient Intelligence and Humanized Computing*, Vol. 12, No. 2, 2053-2063, doi:10.1007/s12652-020-02304-4

[13] Li, J.-Q.; Sang, H.-Y.; Han, Y.-Y.; Wang, C.-G.; Gao, K.-Z. (2018). Efficient multi-objective optimization algorithm for hybrid flow shop scheduling problems with setup energy consumptions, *Journal of Cleaner Production*, Vol. 181, 584-598, doi:10.1016/j.jclepro.2018.02.004

[14] Ning, T.; Wang, X. P.; Hu, X. P. (2019). Disruption management decision model for vehicle scheduling under disruption delay, *Systems Engineering – Theory & Practice*, Vol. 39, No. 5, 1236-1245, doi:10.12011/1000-6788-2017-1335-10

[15] Ning, T.; Wang, X.-P. (2018). Study on disruption management strategy of job-shop scheduling problem based on prospect theory, *Journal of Cleaner Production*, Vol. 194, 174-178, doi:10.1016/j.jclepro.2018.05.139

[16] Feldman, D.; Contreras, S.; Karlin, B.; Basolo, V.; Matthew, R.; Sanders, B.; Houston, D.; Cheung, W.; Goodrich, K.; Reyes, A.; Serrano, K.; Schubert, J.; Luke, A. (2016). Communicating flood risk: looking back and forward at traditional and social media outlets, *International Journal of Disaster Risk Reduction*, Vol. 15, 43-51, doi:10.1016/j.ijdrr.2015.12.004

[17] Liu, C.; Xu, Z.; Zhang, Q.; Zhang, L.; Yao, K. (2020). Green scheduling of flexible job shops based on NSGA-II under TOU power price, *China Mechanical Engineering*, Vol. 31, No. 5, 576-585, doi:10.3969/j.issn.1004-132X.2020.05.010

[18] Huo, H.; Wang, H. B.; Zhang, D. D. (2021). Production management and control based on ant colony optimization and neural network, *International Journal of Simulation Modelling*, Vol. 20, No. 1, 158-169, doi:10.2507/IJSIMM20-1-CO1

[19] Ning, T.; Duan, X.; An, L. (2021). Study on the strategy of multimodal transportation of medical aid materials for public health emergencies: a case study basing on COVID-19, *International Journal of Low-Carbon Technologies*, Vol. 16, No. 4, 1244-1253, doi:10.1093/ijlct/ctab046

[20] Sheremetov, L.; Martínez-Muñoz, J.; Chi-Chim, M. (2018). Two-stage genetic algorithm for parallel machines scheduling problem: cyclic steam stimulation of high viscosity oil reservoirs, *Applied Soft Computing*, Vol. 64, 317-330, doi:10.1016/j.asoc.2017.12.021

[21] Shi, D. L.; Zhang, B. B.; Li, Y. (2020). A multi-objective flexible job-shop scheduling model based on fuzzy theory and immune genetic algorithm, *International Journal of Simulation Modelling*, Vol. 19, No. 1, 123-133, doi:10.2507/IJSIMM19-1-CO1

[22] Amjad, M. K.; Butt, S. I.; Anjum, N.; Chaudhry, I. A.; Faping, Z.; Khan, M. (2020). A layered genetic algorithm with iterative diversification for optimization of flexible job shop scheduling problems, *Advances in Production Engineering & Management*, Vol. 15, No. 4, 377-389, doi:10.14743/apem2020.4.372