Research Article

Dynamic Data Scheduling of a Flexible Industrial Job Shop Based on Digital Twin Technology

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Aiming at the problems of premature convergence of existing workshop dynamic data scheduling methods and the decline in product output, a flexible industrial job shop dynamic data scheduling method based on digital twin technology is proposed. First, digital twin technology is proposed, which provides a design and theoretical basis for the simulation tour of a flexible industrial job shop, building the all-factor digital information fusion model of a flexible industrial workshop to comprehensively control the all-factor digital information of the workshops. A CGA algorithm is proposed by introducing the cloud model. The algorithm is used to solve the model, and the chaotic particle swarm optimization algorithm is used to maintain the particle diversity to complete the dynamic data scheduling of a flexible industrial job shop. The experimental results show that the designed method can complete the coordinated scheduling among multiple production lines in the least amount of time.

1. Introduction

The job shop dynamic data scheduling problem is a typical combinatorial optimization problem and one of the key problems to be considered in flexible industrial production management technology [1]. How to find an optimal scheduling scheme that meets the constraints is the basis and key to improving the production efficiency of a flexible industry. As an extension of classical JSP (Java server page), the flexible job shop dynamic data scheduling problem not only needs to sort the processes on each flexible industrial job shop machine [2] but also needs to select the appropriate machine for each process before sorting, which clearly increases the difficulty of solving flexible job shop scheduling [3]. At present, there are many chemical enterprises with complex systems, uneven information construction levels, and inconsistent data standards. As a typical industry, flexible industrial workshops are facing new situations such as large price fluctuations, high gas supply pressure, and the continuous emergence of new energy. At the same time, the international market competition is becoming increasingly fierce, and environmental control is becoming increasingly strict [4, 5]. For the production data acquisition system of flexible industrial workshops, due to the poor quality of manually collected data and the lack of dynamic data, data communication and sharing have become the bottleneck restricting its development. Nowadays, with the rapid development of social science and technology [6, 7], the flexible industry is also facing the situation of diversified demand and technology improvement. In addition, the dynamic data scheduling of a flexible job shop often involves multiple conflicting optimization objectives [8], and it is difficult to choose between them. Therefore, scholars have conducted a great deal of research on this aspect.

Reference [9] proposed multiobjective job shop scheduling using a multipopulation genetic algorithm. The job shop scheduling problem is a challenging scheduling and optimization problem in the field of industry and engineering. It is related to the work efficiency and operation cost of the factory. The completion time of all jobs is the most common optimization goal in the existing work. A multi-objective job shop scheduling approach is proposed for the first time. The job shop scheduling considers five objectives, which makes the model more practical in terms of reflecting
the various needs of the factory. To optimize these five objectives at the same time, a new genetic algorithm method based on a multipopulation and multiobjective framework is proposed. First, five groups are used to optimize the five objectives, respectively. Second, to avoid each group only focusing on its corresponding single goal, a file-sharing technology is proposed to store the elite solutions collected from the five groups so that the group can obtain optimization information about other goals from the files. Third, an archive update strategy is proposed to further improve the quality of the solution in the archive. Test cases from widely used test sets are used to evaluate performance. Reference [10] proposed a new method to solve the energy-efficient dynamic data scheduling problem. Using the improved unit-specific event time representation, a new mathematical formula for energy-efficient and energy-saving flexible job shop scheduling is proposed, and then the flexible job shop is described using the state task network. Compared with the existing models with the same or better solutions, the model can save 13.5% of the calculation time. In addition, for large-scale examples that cannot be solved by the existing models, this method can generate feasible solutions. Although the above methods have made some progress, they cannot meet the requirements of diversified market demand. In the face of multiple production lines in the multiuser, small batch, and personalized customization mode, problems include the complex calculation process, low real-time efficiency, narrow application range, and unsuitability for wide promotion and use. Therefore, a new dynamic data scheduling method of flexible industrial job shop based on digital twin technology is proposed. In this method, first, the digital twin technology is proposed, and at the same time, the full element digital information fusion model of the flexible industrial workshop is constructed to comprehensively control the full element digital information of the flexible industrial workshop. Then the cloud model is introduced to propose a CGA algorithm, which is used to solve the model, and the chaotic particle swarm optimization algorithm is used to maintain the particle diversity, so as to complete the dynamic data scheduling of flexible industrial job shop. The innovation of the design method is to select the digital twin technology, which provides the design basis and theoretical basis for the simulation inspection of the flexible industrial workshop. The dynamic data scheduling of the flexible industrial workshop is completed with the objective of minimizing the completion time and maximizing the utilization of the production line. Experimental results show that this method has ideal scheduling efficiency and scheduling ability and can spend the least time to complete the coordinated scheduling among multiple production lines.

2. Dynamic Data Scheduling of the Flexible Industrial Job Shop Based on Digital Twin Technology

2.1. Digital Twin Technology. The rise of Internet technologies such as cloud computing has led to the rapid development of the industry, thus promoting the development of the intelligent industry [11, 12]. The interaction and integration of industrial physical structures and information networks have attracted increasing attention. Digital twin technology integrates the physical model, operation, and maintenance data into an information body to obtain multidimensional and multiinformation simulation data into the information body. The physical object can be reproduced in the information virtual space. Through the information interaction, the product R&D and design, production services, and other aspects can be monitored and analyzed to reduce production costs and improve product competitiveness.

The digital twin technology provides the design basis and theoretical basis for the simulation inspection of the flexible industrial workshop [13]; however, safety hazards in the workshop can occur from time to time. The digital twin technology is used to establish the dynamic data scheduling model of the virtual flexible industrial workshop; access the main control, auxiliary control, security, and other equipment detection points in the flexible industrial workshop; and collect various types of status information in real time. It is not necessary for the transportation inspection personnel to go to the site of the flexible industrial operation workshop in order to master the operation status of the flexible industrial operation workshop, provide reliable support for the workshop to realize “continuous equipment inspection,” provide timely warnings of abnormal equipment in the workshop, and prolong the service life of the equipment. Combined with the current workshop operation, the operation principle of the digital twin line is given, as shown in Figure 1.

When the workshop equipment is running, the service system controls the physical production line to carry out the actual production activities according to the production plan; at the same time, the twin production line maps the production operations in real time according to the real-time data of the entity; the results of analysis and calculation can be fed back into the service system in the future for alarm, control optimization, and prediction analysis of the production process. The flexible industrial operation model is constructed according to the digital twin technology [14]. The mapping between the digital space and the physical space of the industrial equipment is divided into three parts: equipment, environment, and system. The workshop equipment maps the actions, spatial positions, and working states of robots, AGVs, processing equipment, and other equipment on the production line in real time to complete the processing process of each station.

2.2. The Factor Digital Information Fusion Model of the Flexible Industrial Workshop. To realize the digital information management of all elements and states in the flexible industrial workshop and to realize the real scene construction of digital twin equipment in the flexible industrial workshop, first, the feature classification and adaptive scheduling model of all-factor digital information in a flexible industrial job shop is constructed. The multidimensional and panoramic power grid virtual real fusion analysis method is adopted, combined with the quantitative regression statistical analysis method to realize the digital twin data fusion and regression analysis of the real scene.
space of the flexible industrial workshop, and the digital twin application construction realizes the integration of the “physical flexible industrial workshop” and the “virtual flexible industrial workshop” [15].

Digital technology is used to perceive and understand the digital information of all elements and states of the flexible industrial workshop, to optimize the characteristics of all elements and states of a real flexible industrial workshop, to build the digital information integration model of all elements and states of the flexible industrial workshop in combination with the four-tier architecture design, and to realize the information management of the industrial workshop in combination with three-dimensional visual management technology. The total element digital information fusion model of the flexible industrial workshop based on digital twin technology is obtained, and the structure is shown in Figure 2.

According to the all-factor digital information fusion model of the flexible industrial workshop based on digital twin technology shown in Figure 2, the fusion data are analyzed through threshold judgment. The information fusion layer is video image fusion. In the all-factor digital information fusion of the flexible industrial workshop, the data exchange process is realized through the data flow. Through the multidimensional sensing device, the multidimensional information, environmental geographic information, and weather state information are extracted to realize the functions of digital twin technology control, equipment monitoring, abnormal alarm, and life prediction, and to determine the all-factor digital information fusion model of the flexible industrial workshop.

2.3. Comprehensive Control of All Digital Information Elements in the Flexible Industrial Workshop. Based on the above analysis, to realize the comprehensive control of all-factor digital information in flexible industrial workshops, digital twin technology is introduced. The key to digital twin technology is that the mathematical model can widely access the information of the physical production line and then drive the management and control of the research objects. The digital twin technology in the study carries out multidimensional management and control of all-factor digital information of the flexible industrial workshop. Its management and control structure is shown in Figure 3.

In the application of digital twin technology to all-factor digital information in flexible industrial job shops, priority scheduling is first used to realize the priority fusion sorting of all-factor digital information mining in flexible industrial job shops, which is recorded as follows:

\[ G_V = (g_{v1}, g_{v2}, \ldots, g_{vn}) \]  

where \( g_{v1}, g_{v2}, \ldots, g_{vn} \) all represent priority fusion sorting sequence values. According to the detection statistical analysis results of the all-factor digital information of the flexible industrial workshop, the output fuzziness of all-factor digital mining is obtained to complete the comprehensive control of the workshop digital information.

3. Realizing the Dynamic Data Scheduling of Flexible Industrial Job Shops

3.1. Construction of the Buffer Area Layout Model of the Flexible Industrial Workshop. The layout of the buffer area of the flexible industrial workshop is mainly analyzed and studied from the workshop conditions to obtain the best local optimization scheme of the buffer area of the flexible industrial workshop, to ensure the maximum improvement of the increased production and benefits.

It is assumed that the operation area required by workshop facilities is determined through layout data analysis, and the operation area of each area needs to be calculated in detail. Among them, the process of determining the working area of workshop facilities is shown in Figure 4.

The workshop facility job buffer plays an essential role in the manufacturing system. In addition to completing the storage function of the layout model, it also needs to support different operations of the layout model, mainly including receiving and storage.
This paper analyzes the operation characteristics of the facility operation buffer area in a flexible industrial workshop. Generally, the buffer area is divided into several different functional areas, mainly including the following aspects:

(1) Production area  
(2) Sorting area  
(3) Distribution area  
(4) Waiting area

Through the above analysis, the layout optimization model of the workshop facility job buffer area is described as follows. Multiple work units with known dimensions are placed in the plane of the known workshop facility work buffer area, mainly to make the layout of each work unit more reasonable. In addition, to effectively facilitate handling, it is necessary to reserve a certain activity space and aisle width for the staff of the flexible industrial workshop. At the same time, some constraints need to be considered in the layout of the buffer area.
In the process of optimizing the layout of the facility operation buffer area in a flexible industrial workshop, the following operation steps are mainly included:

**Step 1: Preparation of raw materials.** In the process of buffer layout optimization, it is necessary to determine five basic elements such as product, output, and handling path. At the same time, the functional area is divided on the basis of the operation unit, and the area and shape of the best operation area are obtained by means of decomposition or combination.

**Step 2: Dynamic data scheduling and relationship analysis between operating units.** Material handling and loading and unloading in flexible industrial workshops are the main causes of operation costs, so layout optimization plays an essential role in the process of dynamic data scheduling. Through the above analysis, it is necessary to analyze the relationship between dynamic data scheduling and various operation units. **Step 3: Calculate the floor area of each unit.** Analyze different factors such as equipment and personnel, obtain the floor area of the operation unit through the operation area calculation formula, and ensure that the calculated area and the actual available area match each other.

**Step 4: Draw the correlation diagram of the unit area of operation.** Calculate the load of the actual area of the operation unit with the corresponding position correlation diagram.

**Step 5: Revise.** Combined with the actual limited conditions, the area of the correlation map is adjusted in real time, and several feasible schemes are formulated at the same time.

**Step 6: Scheme evaluation and selection.** For a feasible scheme, it is necessary to evaluate professional technology, cost, and other aspects, modify the scheme through comparison and analysis, and obtain the final layout scheme.

Based on the above operations, the layout of the workshop facility job buffer can be described as follows:

(1) **Objective function:** The minimum material handling moment \( D_{\text{min}} \) of the flexible industrial workshop and the adjacency correlation degree of different workshops in the maximum buffer area are taken as the max \( D \) objective function. The specific expression is shown in the following formula:

\[
\begin{align*}
\min D &= \int_{i=1}^{n} \int_{j=1}^{n} d_{ij}e_{ij}, \\
\max D &= W_q - \int_{i=1}^{n} \int_{j=1}^{n} f_{ij}h_{ij},
\end{align*}
\]

where \( n \) represents the total number of operating units; \( d_{ij} \) and \( e_{ij} \), respectively, represent the average dynamic data scheduling amount and the total dynamic data scheduling amount between \( i \) and \( j \) of the operation unit; \( W_q \) represents any constant; and \( f_{ij} \) and \( h_{ij} \) represent the material handling speed and time between \( i \) and \( j \), respectively.

(2) The constraints are

\[
\begin{align*}
\left| A_i - A_j \right| + C_{ij} &\geq \frac{x_i + x_j}{2} + B_{xij}, \quad i = 1, 2, \ldots, n - 1, \ j = i + 1, \ldots, n, \\
\left| B_i - B_j \right| + W_q \left( 1 - C_{ij} \right) &\geq \frac{y_i + y_j}{2} + B_{xij}, \quad i = 1, 2, \ldots, n - 1, \ j = i + 1, \ldots, n.
\end{align*}
\]

![Flow chart for determining the area of the workshop facility operation buffer area.](image-url)
where \( C_{ij} \) represents the correlation function between activities; \( x_i \) and \( x_j \) represent the \( i \) and \( j \) activities, respectively; \( y_i \) and \( y_j \) represent the length and width of the activity, respectively; and \( B_{xij} \) represents the handling function between each activity.

The buffer area layout model of the flexible industrial workshop is given by using the following formula:

\[
P_{mx} = \min D + \max D - \left( \frac{x_i + x_j}{2} + B_{xij} \right) - \left( \frac{y_i + y_j}{2} + B_{xij} \right)
\]  

(4)

3.2. Model Solution Based on the CGA Algorithm. The cloud model is mainly characterized by expected value, entropy, and super entropy. The traditional genetic algorithm needs to use empirically specified or fixed crossover and mutation probability for research. The detailed operating principle is that when the average fitness of the population is greater than the individual, the better individual needs to be reported as the fitness value increases; at the same time, better individuals are formed.

According to the characteristics of the normal cloud model, the disadvantages of the genetic algorithm for dynamic data scheduling of the flexible industrial job shop can be effectively improved. The calculation process of the CGA (compact genetic algorithm) algorithm is as follows:

\[
P_{abc} = \begin{cases} 
0.16 \left( \frac{f - \text{Ex}}{\text{En} \cdot \text{f}} \right), & f > 0, \\
0.3, & f < 0,
\end{cases}
\]

(5)

\[
P_{nrd} = \begin{cases} 
0.16 \left( \frac{f - \text{Ex}}{\text{En} \cdot \text{f}} \right), & f \geq 0, \\
0.4, & f < 0.
\end{cases}
\]

(6)

where \( P_{abc} \) and \( P_{nrd} \) represent the overall and local optimal solutions, respectively, and \( o_1, o_2, o_3, \) and \( o_4 \) represent the control parameters, respectively; \( f \) indicates fitness value; and \( \text{Ex} \) and \( \text{En} \) represent the fitness values of the variant individuals. The detailed operation steps of the CGA algorithm are given in Figure 5.

The CGA algorithm is used to solve the layout model of the facility job buffer area in a flexible industrial job shop. The detailed operation steps are as follows:

Step 1: Initialize the population
Step 2: Calculate the fitness value of different individuals
Step 3: Select, copy, and migrate
(1) Copy the best individual to the next generation
(2) Replicate the elite population
(3) The worst individuals will be eliminated and replaced by randomly formed foreign individuals
Step 4: Cross and mutate all elite groups:
(1) The membership degree is randomly formed according to the uniform distribution
(2) The fitness value is determined by both parents
(3) Determine the search scope of different variables
Step 5: Perform the mutation operation:
(1) The workpiece set to be processed is \( K = (k_1, k_2, \ldots, k_n) \), and \( k_n \) is the \( n \) workpiece to be processed
(2) The machine set capable of processing is \( M = (m_1, m_2, \ldots, m_m) \), and \( m_m \) is the \( m \) machine

3.3. Realize the Dynamic Data Scheduling of the Flexible Industrial Job Shop

3.3.1. The Flexible Industrial Job Shop Dynamic Data Scheduling Problem. The flexible industrial job shop dynamic data scheduling problem determines the processing order of workpieces on each workshop machine through a certain optimization strategy so as to minimize the dynamic data scheduling time of the flexible industrial job shop. The corresponding known conditions are described as follows:

(1) The workpiece set to be processed is \( K = (k_1, k_2, \ldots, k_n) \), and \( k_n \) is the \( n \) workpiece to be processed
(2) The machine set capable of processing is \( M = (m_1, m_2, \ldots, m_m) \), and \( m_m \) is the \( m \) machine

![Figure 5: Operation flow chart of the CGA algorithm.](image-url)
(3) The operation sets \( J = (J_1, J_2, \ldots, J_n) \), \( J_i = (j_{i1}, j_{i2}, \ldots, j_{ik}, \ldots, j_{in}) \), and \( J_m \) of each workpiece represent the first operation of the \( i \) workpiece.

The dynamic data scheduling problem of a flexible industrial job shop must meet the following two constraints:

(1) Each operation must be processed in the next operation, and the processing priority of each workpiece is the same.

(2) Each process will not be interrupted by another process during processing.

3.3.2. Dynamic Data Scheduling Solution of the Flexible Industrial Job Shop Based on the Chaotic Particle Swarm Optimization Algorithm. Particle coding is the first problem to be solved in the dynamic data scheduling of a flexible industrial job shop. The particles are decoded to obtain the optimal scheduling scheme. For a \( 3 \times 3 \) flexible industrial job shop dynamic data scheduling problem, each particle is composed of \( 3 \times 3 \) bits. It is composed of 3 bits, and its particle code is set as follows: \([1, 1, 1, 2, 2, 2, 3, 3, 3]\). The processing sequence of each workpiece is shown in Figure 6.

As shown in Figure 6, according to the completion time objective of dynamic data scheduling optimization of the flexible industrial workshop, the particle fitness function of the chaotic particle swarm optimization algorithm is designed, and the corresponding fitness function is defined as follows:

\[
F_{\text{asf}} = \frac{100 \times E_{\text{opt}}}{T_i \times J_m}, \tag{7}
\]

where \( E_{\text{opt}} \) represents the fitness function coefficient, \( T_i \) represents all operation times of the machine, and \( J_m \) represents the completion time after decoding the \( m \) particle line. Particle swarm aggregation is very serious; in the process of multiple iterations, the optimal particle has no change or little change. The specific operations of chaotic operations are explained as follows.

The fitness variance \( \sigma^2 \) of particle swarm is calculated as shown in the following formula:

\[
\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{F_i - F_{\text{avg}}}{F} \right)^2, \tag{8}
\]

where \( F_{\text{avg}} \) represents the average fitness value of the current particle swarm, \( F_i \) represents the fitness value of the \( i \) particle, and \( F \) represents the total number of particle swarms. If \( \sigma^2 < 1 \), the particle swarm has serious aggregation and premature convergence. Some small particles are chaotic until the termination conditions are met, and the optimal solution is output to complete the dynamic data scheduling of a flexible industrial job shop based on digital twin technology.

![Figure 6: Dynamic data scheduling scheme of the \( 3 \times 3 \) flexible industrial job shop.](image)

| Machine number | Workpiece serial number |
|----------------|-------------------------|
| R1             | 2 3 1                   |
| R2             | 2 1 3                   |
| R3             | 3 2 1                   |

Table 2: Comparison of resource allocation results of three algorithms scheduling.

| Production line | 1 | 2 | 3 | 4 | 5 |
|-----------------|---|---|---|---|---|
| Number of workpieces | 20 | 30 | 20 | 25 | 30 |
| Number of machines | 20 | 15 | 20 | 20 | 20 |
| C++             | 920 1,155 935 1,036 1,208 |
| Paper method    | 918 1,158 940 1,035 1,210 |
| Reference [9] method | 928 1,165 955 1,064 1,231 |
| Reference [10] method | 901 1,267 980 1,143 1,341 |

Note: \( C^* \) in Table 2 represents the Pareto optimal solution, which refers to the optimal resource scheduling result in an ideal state, and \( C^* \) represents the optimal solution obtained after 50 iterations of each method.

4. Experimental Analysis

To verify the effect and feasibility of flexible industrial job shop dynamic data scheduling based on digital twin technology, experiments were carried out to compare our approach with the methods in references [9, 10]. The dynamic data and parameters of the flexible industrial workshop refer to a large machinery production workshop in the old industrial base in Northeast China. C++ and OpenCV2.2 were used to build a simulation experiment environment. The experimental parameters were set as shown in Table 1.

In the large-scale machinery production workshop, there are a large number of production lines, a large scheduling
scale, and very strict requirements for product output. In this paper, 10 production lines are selected. On the premise that the number of workpieces and machines are different, the methods of this paper, references [9, 10] are used to schedule and adjust the production lines. The results are shown in Table 2.

It can be seen from Table 2 that among the three methods, the resource allocation result of this method after scheduling is closest to the Pareto optimal solution, which proves that the method can reasonably schedule tasks according to the number of workpieces and machinery, keep the machine on all the time, avoid outages caused by unreasonable resource scheduling, and save production time.

Experiments were carried out to verify the balance of the multiproduction line coordinated scheduling of the three methods, to verify which algorithm can avoid uneven division of labor, partial idleness, and partial work. The evaluation indexes are the maximum completion time and production line load. The experimental results are shown in Figure 7. In Figure 7, the solid line represents the maximum completion time, and the dotted line represents the load of the production line.

As can be seen from Figure 7, the maximum completion time peak appears in the method of reference [9], and the production line load peak appears in the method of reference [10]. The maximum completion time and production line load curves of the two algorithms fluctuate greatly and are generally high. The maximum completion time and production line load curve of our method change gently. This shows that this method has a certain balance for the coordinated scheduling of multiple production lines, can ensure the balanced division of labor of the production line, and will not allow it to be partially idle and partially working.

Combining the two evaluation indexes of maximum completion time and production line load, the income standard of the algorithm can be further evaluated; that is,
the final income is obtained by the machining enterprise by ensuring the coordinated scheduling of the production line. The calculation formula is shown in the following formula:

$$C_{MT}(a_i) = \frac{\min_{a_i \in B_1} [M(a_i)]}{M(a_i)} \times \frac{\min_{a_i \in B_2} [C(a_i)]}{C(a_i)}$$

(9)

where $C$ represents comprehensive income; $B_1 = \{b_1, b_2, b_3\}$ corresponds to the methods in this paper, reference [9], and reference [10], respectively; $M$ represents the maximum completion time; and $C$ represents the line load. We used formula (9) to calculate the comprehensive income of the three methods, and the results are shown in Figure 8.

It can be seen from Figure 8 that the comprehensive income of our method is the highest and most stable, while the other two methods have large fluctuations, which shows that the coordinated scheduling of multiple production lines by our method can maximize the production benefits of flexible industrial operations and result in ideal scheduling efficiency and scheduling ability.

To sum up, the dynamic data scheduling method of the flexible industrial job shop based on digital twin technology has good scheduling performance.

5. Conclusions and Prospects

The innovation of the flexible industrial job shop dynamic data scheduling method based on digital twin technology is that it selects digital twin technology to complete the flexible industrial job shop dynamic data scheduling with the goal of minimizing completion time and maximizing production line utilization. In the flexible industrial workshop, the dynamic data between multiple production lines has always been one of the research focuses. The following conclusions were obtained through the research:

(1) Because of its great complexity, this paper introduces a cloud computing mode to reduce the calculation difficulty and solve the problem of coordinated scheduling among multiple production lines from the perspective of case-based reasoning.

(2) The research shows that the proposed method can complete the coordinated scheduling among multiple production lines in the least amount of time.

Due to the limited time and energy, the proposed method still has shortcomings. The follow-up research will focus on the following aspects:

(1) In the actual layout process, each working area of the facility operation buffer area of the flexible industrial workshop can be of various shapes. In the later research process, the changeable operation problem needs to be considered and solved by relevant algorithms.

(2) Subsequently, the conditional constraints of export location and production location can be added to the all-factor digital information fusion model of the flexible industrial workshop to comprehensively analyze the impact of different constraints on the optimization results.

(3) Because the service life of different products is completely different and the types of products are becoming increasingly complex, the layout optimization of the facility job buffer in a flexible industrial job shop could be studied in the future.

Data Availability

The data for all figures used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] J. Moreno, M. Hornberger, M. Schmid, and G. Scheffknecht, “Part-load operation of a novel calcium looping system for flexible CO2 capture in coal-fired power plants,” Industrial & Engineering Chemistry Research, vol. 60, no. 19, pp. 7320–7330, 2021.

[2] E. Spyrakos-Papastavridis and J. S. Dai, “Minimal model-based trajectory tracking and variable impedance control of flexible-joint robots,” IEEE Transactions on Industrial Electronics, vol. 5, no. 99, pp. 1–8, 2020.

[3] L. C. Bree, A. Bulan, R. Herding et al., “Techno-economic comparison of flexibility options in chlorine production,” Industrial & Engineering Chemistry Research, vol. 59, no. 26, pp. 12186–12196, 2020.

[4] F. Zolfagharpour, B. Saghafian, and M. Delavar, “Adapting reservoir operation rules to hydrological drought state and environmental flow requirements-sciencedirect,” Journal of Hydrology, vol. 600, no. 9, Article ID 126581, 2021.

[5] A. H. Dehghanipour, G. Schoups, B. Zahabiyoum, and H. Babazadeh, “Meeting agricultural and environmental water demand in endorheic irrigated river basins: a simulation-optimization approach applied to the Urmia Lake basin in Iran,” Agricultural Water Management, vol. 241, no. 1, pp. 15–23, 2020.

[6] A. Stange, D. K. Campbell, and D. J. Bishop, “Science and technology of the Casimir effect,” Physics Today, vol. 74, no. 1, pp. 42–48, 2021.

[7] B. R. Lawn, “Chipping: a pervasive presence in nature, science and technology,” Journal of Materials Science, vol. 56, no. 10, pp. 12186–12196, 2020.

[8] C. Huang, H. Wang, D. Guo et al., “A dynamic priority strategy for IoV data scheduling towards key data,” The Journal of Supercomputing, vol. 77, no. 2, pp. 2018–2032, 2021.

[9] S. C. Liu, Z. G. Chen, Z. H. Zhan, S. W. Jeon, S. Kwong, and J. Zhang, “Many-objective job-shop scheduling: a multiple populations for multiple objectives-based genetic algorithm
[10] N. Rakovitis, D. Li, N. Zhang, J. Li, and X. Xiao, "Novel approach to energy-efficient flexible job-shop scheduling problems," *Energy*, vol. 2021, no. 5, Article ID 121773, 2021.

[11] J. Ruuskanen, T. Berner, K. E. Arzén, and A. Cervin, "Improving the mean-field fluid model of processor sharing queuing networks for dynamic performance models in cloud computing," *Performance Evaluation*, vol. 151, no. 11, Article ID 102231, 2021.

[12] G. J. Mirobi and L. Arockiam, "DAVmS: distance aware virtual machine scheduling approach for reducing the response time in cloud computing," *The Journal of Supercomputing*, vol. 77, no. 6, pp. 1–12, 2021.

[13] B. Elahi and S. A. Tokaldany, "Application of internet of things-aided simulation and digital twin technology in smart manufacturing," *Advances in Mathematics for Industry 4.0*, vol. 12, no. 12, pp. 335–359, 2021.

[14] C. Ruzsa, "Digital twin technology-external data resources in creating the model and classification of different digital twin types in manufacturing," *Procedia Manufacturing*, vol. 54, no. 1, pp. 209–215, 2021.

[15] V. A. Dolgov, P. A. Nikishechkin, V. E. Arkhangelskii, P. I. Umnov, and A. A. Podkidyshhev, "Models for managing production systems of machine-building enterprises based on the development and using of their digital twins," *EPJ Web of Conferences*, vol. 248, no. 4, Article ID 04015, 2021.