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PRODUCTION SCHEDULING OPTIMIZATION OF FLEXIBLE MANUFACTURING SYSTEM FOR GREEN MANUFACTURING

Panpan Xu[1, *] and Jinfeng Wang[2]

[1]School of Economics and Management
Shanghai Maritime University,
Shanghai, China
[*]Corresponding author's e-mail: amurokyo@msn.com

[2]Institute of FTZ Supply Chain
Shanghai Maritime University
Shanghai, China

The manufacturing industry is the economic pillar of the country, which can provide a large number of jobs and alleviate the employment pressure. In the manufacturing industry, the scheduling problem is the core problem of manufacturing intelligence and automation. Scheduling plays an extremely important role in the productivity as well as reliability of large-scale complex production systems. Therefore, a production scheduling method based on a genetic algorithm is proposed, which first uses a genetic algorithm to achieve scheduling optimization. Then, the minimizing carbon emission method is introduced to achieve green manufacturing. Finally, the production scheduling system (PSS) of flexible manufacturing form is constructed. The experimental results show that the proposed production scheduling method has a better scheduling optimization effect. The resource utilization rate reaches 0.884, and the workpiece processing time is reduced to 0.32s. The carbon emission cost is significantly lower than that of the traditional production scheduling system. The results show that using genetic algorithms to optimize the production scheduling of flexible manufacturing systems is feasible. It can improve production efficiency while reducing carbon emissions. The model proposed in this study can be a good solution to practical problems in industrial production intelligence.

Keywords: Intelligence; Green Manufacturing; FMS; Production Scheduling.

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1. INTRODUCTION

Since the reform and opening up, China's manufacturing industry has shown a sustained positive development trend. However, from the current research status, the flexible manufacturing system of industrial production is still difficult to effectively meet the production demand. Most industrial production consumes a huge amount of electricity, and the pollution generated is more serious. In manufacturing development, production scheduling problems seriously affect production efficiency (Jerbi *et al*., 2019). For the production scheduling problems in the manufacturing industry, there are a large number of studies that have put forward coping strategies, including control optimization of the production scheduling system, as well as equipment renewal of the system (Sarkar and Bhuniya, 2022). In addition, to meet the dynamic management of flexible manufacturing systems, some studies have proposed system architecture strategies (Wang *et al*., 2021).

For this reason, in this study, the eco-optimization of the flexible manufacturing system is considered in the productivity while making it meet the green manufacturing requirements (Setiawan *et al*., 2019). On this basis, the genetic algorithm is introduced to realize the design of the production scheduling optimization system. Genetic algorithms can directly perform operations on structural objects. Therefore, there are restrictions on the derivation and continuity of function. It has hidden parallelism and better global search optimization ability. The genetic algorithm does not rely on the gradient information in the global search and optimization search but only needs the objective function of the search direction and the corresponding fitness function. Then, the carbon emission minimization strategy is proposed to realize the production scheduling optimization in the context of green manufacturing. This research can provide some reference for scheduling problems in industrial production. For example, the method proposed in the study improves scheduling efficiency by reducing scheduling time. At the same time, it has a better ability to respond to emergency situations. The method of minimizing carbon emissions

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can reduce the power and carbon emission costs of system operation.

2. RELATED WORKS

A flexible manufacturing system is an information-based intelligent manufacturing system proposed to meet industrial automated production. With the development of intelligence, the research on flexible manufacturing systems is increasing. Dai *et al*. (2019) found that the traditional flexible manufacturing system has a complex structure and low reliability. To address this problem, the research team proposed a temporal multilayer network structure. It can describe the production process more clearly and evaluate the resource nodes in the production task. The results show that the proposed network structure can effectively evaluate the energy consumption in the production process and measure the time-dependent performance of the system. Sim (2019) found that the traditional intelligent manufacturing system cannot meet the field production system. To address this problem, the research team proposed a six-step model. The flexible manufacturing system is integrated to improve the function. The research results show that on the production line, the proposed model can effectively improve the product production effect as well as production efficiency and reduce the delivery cycle time by 50%. Hu *et al*. (2020) believed that the existing scheduling strategy is not well adapted to the processing of high-throughput data in the modern smart factory.

To address this problem, the research team optimized the graph convolutional network. With the help of the optimized algorithm, the dynamic scheduling of the flexible manufacturing system is achieved. Considering the production efficiency, the Petri nets are introduced. The results of the study show that the proposed method can effectively improve manufacturing efficiency and achieve dynamic scheduling of flexible manufacturing systems. Lugaresi *et al*. (2020) found that the existing techniques of production planning and control decision-making through simulation online are more difficult to implement in real systems.

In order to address this problem, the research team proposed a manufacturing system model that can simulate the control of real production processes. It can be used to effectively achieve the production process capture. The model is applied to the flexible manufacturing system to verify the feasibility. The research results show that the proposed model can effectively reduce the expected duration and improve production efficiency. In the development of manufacturing towards intelligent manufacturing, Ocampo-Martinez *et al*. (2020) found that the main goal is the energy efficiency and flexibility of manufacturing. However, existing manufacturing systems cannot meet such requirements with lower computational power. To address this issue, the research team proposed a control strategy for flexible manufacturing systems. The system is optimized by considering the energy consumption constraint behavior during the production process. The results show that the control strategy proposed by the research has less impact on productivity, which can effectively reduce energy consumption.

Production scheduling in industrial manufacturing is a key technology to improve production efficiency, which has been explored by a large number of scholars. Cao *et al*. (2020) found that the traditional scheduling scheme needs to be reconstructed and optimized when there is a lack of relevant cases in the case base. It will consume a large amount of resources and costs. To address this problem, the research team proposed a production scheduling optimization method, which is able to optimize the scheduling of production raw materials. Moreover, in the study, the team members proposed a scheduling strategy for resource and cost consumption. The experimental results show that this strategy can significantly reduce the burden in modeling and production scheduling. Remigio *et al*. (2020) argued that fluctuations in the market and the price of electricity can pose a serious challenge to traditional plant decision-making. Therefore, the research team proposed a dynamic production scheduling decision for production control through constraint modeling. Finally, the effectiveness of this method is verified through experiments. It is shown that the proposed system can effectively achieve dynamic real-time optimization, and the effectiveness in production scheduling is also evident. In order to solve the scheduling problem in the production line, Soler *et al*. (2021) proposed a mathematical model based on shared resources, which can discuss production factors such as cost and inventory. In the results, it is shown that the production scheduling model proposed by the study is able to solve the resource scarcity problem on the production line, achieving production scheduling optimization. In the existing scheduling studies, Wang *et al*. (2021) found that machines are assumed to be continuously available. However, in the real world, they may be unavailable for a period of time for the sake of protecting the machines. To address this problem, the research team developed a multi-objective optimization production scheduling model, which is used for flexible shop floor production scheduling. Taking into account transportation and maintenance during the production process, the genetic algorithms is introduced to enhance the model scheduling optimization capability. The results of the study show that the proposed production scheduling model outperforms other comparison methods. Mansouri *et al*. (2019) argued that the ability to accurately predict a company's output is an extremely important issue for manufacturing companies. To address this issue, the research team proposed a mixed effects model, which can analyze production data from complex workshops. The results of the study show that the model can accurately analyze the production capacity of the shop floor. It can be used to propose scheduling strategies.

In summary, from the current industrial production, a large number of studies have proposed optimization strategies for the flexible manufacturing system. To improve the efficiency of industrial production, a large number of scholars have proposed production scheduling strategies. However, in the current research on flexible manufacturing systems and production scheduling strategies, few studies consider the concept of green production under the development of society, which makes it difficult to control carbon emissions in manufacturing. The genetic algorithm can directly operate on the structural objects. There are no limitations of derivation and function continuity, and it also has hidden parallelism and better global optimization ability. Genetic algorithms do not rely on gradient information in global search and optimization search but only need the objective function of the search direction and the corresponding fitness function. Therefore, genetic algorithm is combined with scheduling models to study scheduling problems in industry. This study can provide a partial reference to the scheduling problems in industrial production. For example, the method proposed in the study improves scheduling efficiency by reducing scheduling time. At the same time, it has a better ability to respond to emergency situations. The method of minimizing carbon emissions can reduce the power and carbon emission costs of system operation.

3. OPTIMIZATION DESIGN OF PSS IN FMS

3.1 Design of Production Scheduling Algorithm under the Background of Green Manufacturing

In the development of intelligent production, industrial manufacturing is also gradually tending to automation. To meet the increasing production needs of users, many manufacturing enterprises are turning to flexible manufacturing (Dolgui *et al*. 2019). To improve the production management capability of flexible manufacturing, a production scheduling scheme is proposed. Considering the requirements of green manufacturing, GA is introduced to design the production scheduling algorithm, thereby improving the stability of production scheduling.

GA is an intelligent algorithm based on natural laws. It relies on individual survival problems, simulates biological genetics in nature, and obtains new populations through selection, crossover, mutation and other operations (Sunar and Birge, 2019; Dai *et al*., 2020). If the obtained population fails to meet the preset conditions, it will enter the cycle and iterate again until the preset conditions are met. Finally, the individual with the highest fitness value will be output (Essien and Giannetti, 2020). The basic calculation flow of GA is shown in Figure 1.

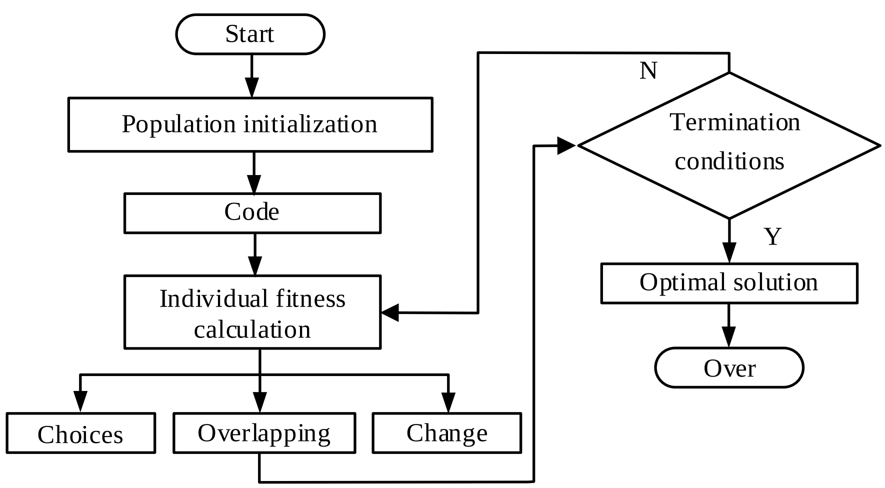


Figure 1. Calculation flow of GA

In Figure 1, the GA will initially set the population size and optimize the population on the basis of meeting the actual needs. To improve the running efficiency of the algorithm, binary coding is used in the population coding, which makes the algorithm easier to implement. After coding, the fitness function is set to calculate the fitness of individuals in the population so as to select individuals and achieve survival of the fittest. In the study, to minimize the error between the optimal value of the output and the expected value, the Frobenius norm of the error matrix is considered as the output of the objective function. The error between the final output optimal value and the expected value is minimized. The specific calculation Equation for the Frobenius norm of the error matrix is shown in Equation (1).

$$\|A\|_F = \left(\sum_{i=1}^{n} |\alpha_i|^2\right)^{\frac{1}{2}} \tag{1}$$

In Equation (1), $\|A\|_F$ is Frobenious norm, and α_i represents the error value between the prediction value and the expected value of the i -th sample. According to the output of the objective function, the ranking fitness function-ranking function is used to calculate the individual fitness value. The mechanism is as follows. When the target value is maximum, the individual fitness value is output. After differential pressure processing, the minimum fitness value is allocated, that is, the minimum target output is allocated with the maximum fitness value (Wang *et al*., 2020).

In the production scheduling of flexible manufacturing, GA is used to achieve global optimization, which aims to minimize the processing completion time of the latest workpiece, that is, to minimize the goal. Therefore, it is necessary to set reasonable fitness, as shown in Equation (2).

$$f = max\{max\{J_{e_i}\}\} \tag{2}$$

In Equation (2), f represents the fitness value. J_{e_i} indicates the end time of production and manufacturing of the i -th workpiece. After setting the fitness value, the crossover operator in the GA needs to be designed to increase the population diversity. Taking the production scheduling in FMS as the research object, the dual segment coding scheme, namely binary coding, is adopted in the research. For binary coding, the POX operator is used to realize the cross-operation of genetic information so as to ensure that the offspring can integrate more complete genetic information.

Secondly, in the production scheduling, to achieve green manufacturing, it is necessary to calculate the carbon emissions of the production workshop and control the carbon emissions. The calculation Equation of carbon dioxide emissions is shown in Equation (3).

$$E = N \times F \tag{3}$$

In Equation (3), E represents carbon dioxide emissions, (t). N refers to energy consumption (m^3). F is the carbon dioxide emission factor, in kg/GJ. After carbon emission calculation, carbon emission is minimized to achieve production scheduling with the lowest carbon emission, as shown in Equation (4).

$$min\, f_1 = min(\sum_{k=1}^{m} U_k \times \alpha_U + \sum_{k=1}^{m} F_k \times \alpha_F) \tag{4}$$

In Equation (4), U_k represents the operating power of the k -th equipment in production. m represents the total number of equipment in production. α_U represents the carbon emission conversion factor during equipment operation. F_k represents the coolant flow required for the operation of production equipment. α_F represents the carbon emission conversion factor of the production equipment coolant. Secondly, to optimize production scheduling, it is necessary to calculate the minimum completion time, as shown in Equation (5).

$$min\, f_2 = min(\, max(\, C_i)) \tag{5}$$

In Equation (5), C_i represents the processing time of the first workpiece. Finally, the production scheduling optimization model based on carbon emissions is shown in Equation (6).

$$min\, f_o = min(\, f_1 + f_2) \tag{6}$$

Equation (6) is used to calculate the carbon emissions in industrial production and analyze the minimum carbon emissions in equipment processing. The workshop production scheduling effect in green production and manufacturing is evaluated.

3.2 Production Scheduling Optimization of FMS

FMS is a key technology in current industrial production, which provides an effective management and production mechanism for workshop production. In addition, the FMS can deploy according to the received order information to improve the production capacity of the workshop (Essien and Giannetti, 2020). However, with the increasing social demand, the requirements for manufacturing industrial workpieces in the market are also increasing. Therefore, the existing FMS is affected by the scheduling strategy. It is difficult to achieve scheduling optimization of production management (Leng *et al.*, 2019; Amiri *et al.*, 2019). In this paper, a production scheduling method based on GA is proposed. Based on this method, a PSS for FMS is proposed. First, the system architecture is constructed. In the system architecture, the system architecture strategy needs to be proposed based on the industrial manufacturing production mode, as shown in Figure 2.

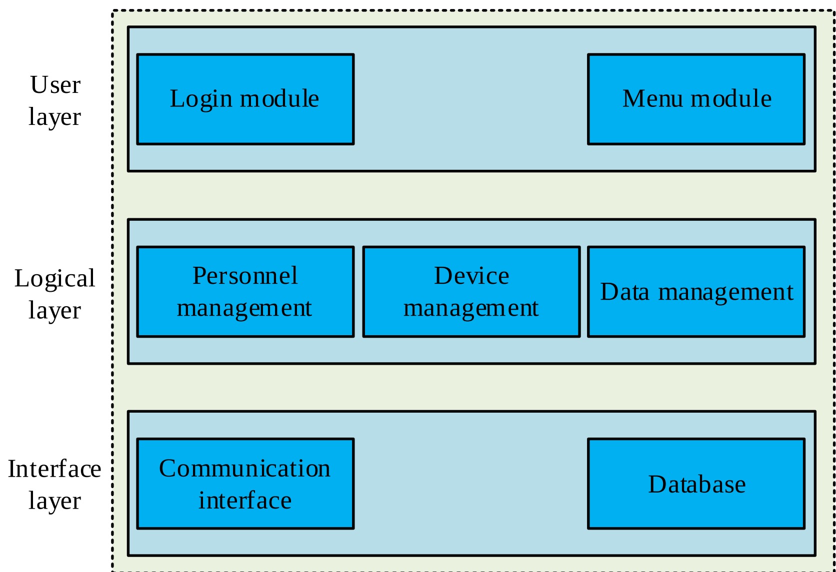


Figure 2. PSS architecture

Figure 2 shows the PSS architecture. It includes the interface layer, logic layer and user layer. The interface layer includes the communication interface and database of the system. The main function of the communication interface is to receive the relevant data of the processing equipment and the processing workpiece so as to generate production information. The main function of the database is to summarize the data collected at the communication interface and to store information by building a database to meet the subsequent operation of the system. In the logic layer, management control is mainly designed for data and workshop personnel. It includes personnel management, equipment management and other management modules. To control equipment and production, data analysis modules are added to process and analyze database information. In the user layer, the system module is mainly designed for managers, including the login module and menu module. The login module is mainly responsible for verifying the information of workshop staff. After verification, the menu module is used to control data and work equipment.

In data processing and analysis, to effectively process the huge production data, the radial basis function (RBF) algorithm is introduced into the PSS to process the huge data. RBF is a machine learning algorithm that has obvious advantages in batch data processing. This algorithm can maintain a high data analysis speed for a long time. It can effectively cope with the growing data in the production process faced in this study (Calzavara *et al.*, 2020). To adapt to the growing data volume in the workshop production, the RBF algorithm is studied for optimal processing. A sliding fixed-length window is introduced and combined with the RBF function to form a windowed online learning data processing model (Kovacova and Lăzăroiu, 2021). In the face of continuously updated dynamic data flow, the number of data samples is no longer a stable batch form. Based on a fixed-length sliding window, data samples slide in an orderly window manner over time. Since the length of the window remains unchanged, when a new data sample enters, it is necessary to delete an existing data sample in the original window (Ding *et al*., 2019). The data processing model is trained through an equal amount of online learning. The data samples in the window are continuously added and deleted. While keeping the data flow updated, the operation time of a single training of the model is unchanged. It can effectively process dynamic streaming big data efficiently.

The sample set of the improved RBF incremental learning algorithm based on the fixed length sliding window is $T = \{x_i, y_i\}_{i=t}^{i=t+m+1}$. The sample set will be updated with the growth of time t. $x(t) = \{x_t, x_{t+1}, \cdots, x_{t+m+1}\}$, $y(t) = \{y_t, y_{t+1}, \cdots, y_{t+m+1}\}^T$, $x_t \in R^n$, $y_t \in R$. m represents the length of the sliding window, and $m = 4$. The RBF function is shown in Equation (7).

$$f(x) = \sum_{i=t}^{t+m+1} \beta_i \varphi(\|x = x_i\|) \tag{7}$$

In Equation (7), φ represents the Gaussian kernel function in the algorithm. β represents the weight of the neuron. At t, the matrix form of RBF kernel function A_t is shown in (8).

$$A_t = \begin{bmatrix} \varphi(\|x_t - x_t\|) & \cdots & \varphi(\|x_t - x_m\|) \\ \vdots & \ddots & \vdots \\ \varphi(\|x_m - x_t\|) & \cdots & \varphi(\|x_m - x_m\|) \end{bmatrix}_{m\times m} \tag{8}$$

The block matrix form of RBF kernel function A_t is shown in Equation (9).

$$\begin{cases} A_t = \begin{bmatrix} h(t) & H(t)^T \\ H(t) & w(t) \end{bmatrix} \\ h(t) = \varphi(\|x_t - x_t\|) \\ H(t) = [\varphi(\|x_{t+1} - x_t\|), \cdots, \varphi(\|x_{t+m-1} - x_t\|)]^T \\ w(t) = \begin{bmatrix} \varphi(\|x_{t+1} - x_{t+1}\|) & \cdots & \varphi(\|x_{t+1} - x_{t+m-1}\|) \\ \vdots & \ddots & \vdots \\ \varphi(\|x_{t+m-1} - x_{t+1}\|) & \cdots & \varphi(\|x_{t+m-1} - x_{t+m-1}\|) \end{bmatrix} \end{cases} \tag{9}$$

In Equation (9), $h(t)$ represents RBF function. $H(t)$ represents the RBF function calculation set. $w(t)$ represents the weight set. T indicates transposition. At $t + 1$, after the new data sample (x_{t+1}, y_{t+1}) enters, the existing data sample (x_t, y_t) is deleted. The matrix form of RBF kernel function A_{t+1} is as follows.

$$A_{t+1} = \begin{bmatrix} \varphi(\|x_{t+1} - x_{t+1}\|) & \cdots & \varphi(\|x_{t+1} - x_{t+m-1}\|) & \varphi(\|x_{t+1} - x_{t+m}\|) \\ \vdots & \cdots & \ddots & \vdots \\ \varphi(\|x_{t+m-1} - x_{t+1}\|) & \cdots & \varphi(\|x_{t+m-1} - x_{t+m-1}\|) & \varphi(\|x_{t+m-1} - x_{t+m}\|) \\ \varphi(\|x_{t+m} - x_{t+1}\|) & \cdots & \varphi(\|x_{t+m} - x_{t+m-1}\|) & \varphi(\|x_{t+m} - x_{t+m}\|) \end{bmatrix} \tag{10}$$

The block matrix form of RBF kernel function A_{t+1} is as follows.

$$\begin{cases} A_{t+1} = \begin{bmatrix} w(t) & V(t)^T \\ V(t+1)^T & f(t+1) \end{bmatrix} \\ f(t+1) = \varphi(\|x_{t+m} - x_{t+m}\|) \\ V(t+1) = [\varphi(\|x_{t+m} - x_{t+1}\|), \cdots, \varphi(\|x_{t+m} - x_{t+m-1}\|)]^T \end{cases} \tag{11}$$

The block matrices A_t^{-1} and A_{t+1}^{-1} used for inversion can be represented as follows.

$$\begin{cases} A_t^{-1} = \begin{bmatrix} 0 & 0 \\ 0 & W(t) \end{bmatrix} + R(t) \cdot R(t)^T \cdot Z(t) \\ A_{t+1}^{-1} = \begin{bmatrix} W(t)^{-1} & 0 \\ 0 & 0 \end{bmatrix} + R(t+1) \cdot R(t+1)^T \cdot Z(t+1) \end{cases} \tag{12}$$

Finally, the RBF algorithm is used to process the production data in the workshop so as to facilitate the production scheduling of the FMS in the workshop.

4. TEST RESULTS OF OPTIMIZATION EFFECT OF PSS

4.1 Performance Analysis of Production Scheduling Algorithm

This study used the SQL Server 2014 database to train and test the model. A production scheduling method based on GA is proposed in this study. Therefore, to evaluate the effectiveness of the algorithm, the production scheduling algorithm is first simulated and analyzed. In the simulation analysis, the initial parameters are set for the GA. To get the simulation results more quickly, the population size is set to 150, which can meet the requirements of multiple types of workpieces and small batches at the same time. In addition, the upper limit of the number of iterations is set to 300. The data search accuracy test results of GA are shown in Figure 3. From Figure 3, the search accuracy of both the Kacem algorithm and GA decreases as the number of iterations increases. Figure 3 (a) shows the change of data search accuracy of the Kacem algorithm. It can be found that after the number of iterations reaches 20, the average search accuracy of the algorithm increases to 84.26%, while the data search accuracy of the optimal solution increases to 91.65%. It remains stable in the accuracy range for a long time in the subsequent iteration calculation. Figure 3 (b) shows the change of GA search accuracy. As the number of iterations increases, the data search accuracy of GA shows an increasing trend. From Figure 3 (a), the average accuracy of the GA reaches 90.07% after 15 iterations, and the optimal solution of the search accuracy reaches 96.62%. The above results show that compared with other algorithms, the designed GA has a higher accuracy in data search. Therefore, it has a higher accuracy when processing the workpiece data in the production workshop.

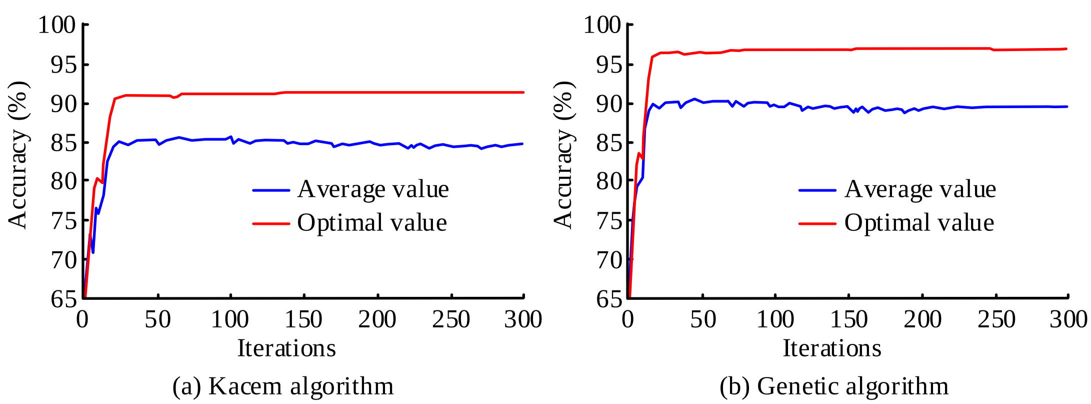
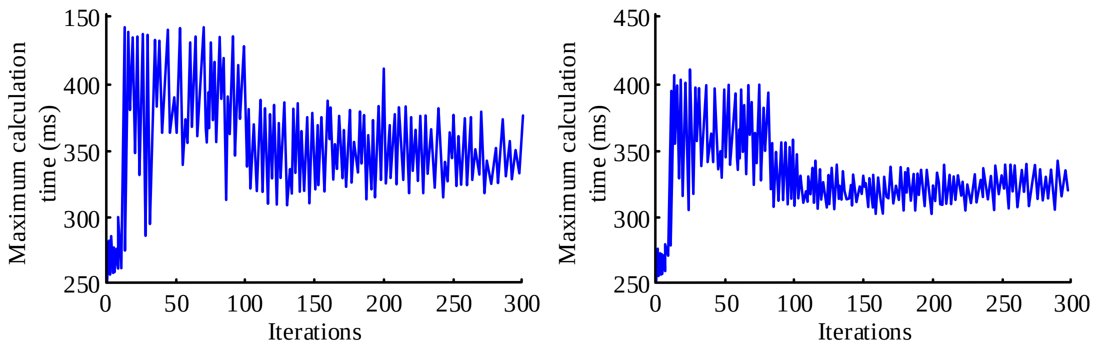


Figure 3. Algorithm search accuracy

After evaluating the search accuracy of the algorithm, the maximum calculation time of the algorithm in operation is studied and evaluated. The results are displayed in Figure 4. Figure 4 shows the maximum calculation time of the two algorithms during 300 iterations. Figure 4 (a) shows the maximum calculation time of the Kacem algorithm. The maximum calculation time of the algorithm shows a downward trend with the number of iterations increasing. In addition, it can be seen that when the number of iterations rises to 100, the maximum calculation time of the Kacem algorithm decreases to less than 400ms and fluctuates around 350ms. Figure 4 (b) shows the maximum calculation time of the GA in the 300 iterations. It can be seen that the maximum calculation time of the algorithm continuously decreases as the number of iterations increases, gradually decreasing to 350ms after 80 iterations. After 100 iterations, the maximum calculation time of the GA is stable around 320ms. The above results show that the maximum calculation time of the designed GA is significantly lower than that of other algorithms. Therefore, the designed genetic algorithm can achieve fast convergence.



(a) Kacem algorithm (b) Genetic algorithm

Figure 4. Maximum calculation time of algorithm

In the performance analysis of GA, to understand the scheduling capability, the application value of the algorithm is analyzed through resource utilization. The simulation results are shown in Figure 5. From Figure 5, with the increase of iterations, the resource utilization of the Kacem algorithm and GA shows a growing trend. Finally, they become stable after the number of iterations reaches 40. It can be seen that the resource utilization of GA shows a decreasing trend after reaching the maximum and then becomes stable when the number of iterations is 50. In addition, from the changes of the two curves, after 30 iterations, the resource utilization rate of GA gradually stabilizes. It is stable near 0.9 and finally decreases to 0.884. Although the resource utilization rate of the Kacem algorithm continues to improve, the stable resource utilization rate of the algorithm is below 0.85. The maximum resource utilization rate of the Kacem algorithm is only 0.849, and the minimum resource utilization rate is reduced to below 0.7. Therefore, although the resource utilization rate of GA shows a downward trend in the iterative learning process, the stable value is still significantly higher than that of the Kacem algorithm. Therefore, GA can achieve effective resource utilization.

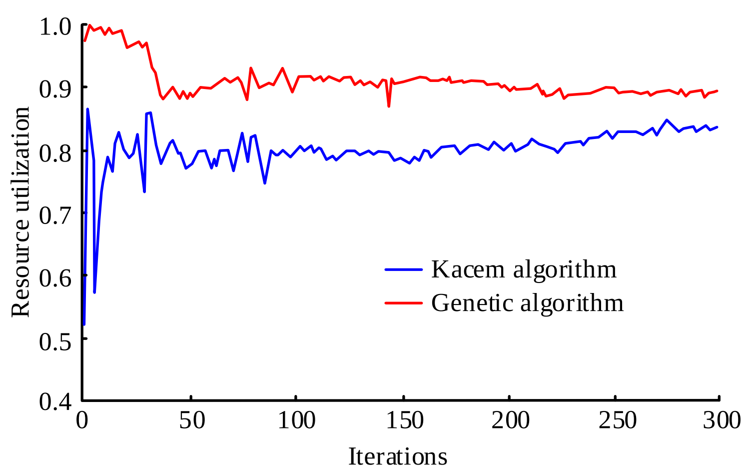


Figure 5. Algorithm resource utilization

In order to further validate the performance of the GA, it is compared with the Kacem algorithm. The F1 value, root mean square error, accuracy and false alarm rate are used in this experiment. In Table 1, the F1 value, root mean square error, accuracy and false alarm rate of the GA algorithm are 0.72, 0.21, 96.37% and 1.7%, respectively. The F1 value, root mean square error, accuracy and false alarm rate of the Kacem algorithm are 0.65, 0.32, 95.58% and 1.89%, respectively. The experimental results show that the proposed model has better performance.

Table 1. Algorithm Performance Comparison

Algorithm	F1	RMSE	Accuracy	False alarm rate
GA	0.72	0.21	96.37	1.7
Kacem	0.65	0.32	95.58	1.89

4.2 Test and Analysis of PSS

The research aims to improve the production scheduling effect in the FMS by designing GA. To analyze the application performance of the PSS, the research first evaluates the processing time changes, as shown in Figure 6. In Figure 6, the difference between the PSS of FMS optimized by the Kacem algorithm and GA and the traditional production scheduling system is compared. From the change of the curve, it can be seen that the processing time of the PSS continuously decreases as the number of iterations increases. Compared with the traditional production scheduling system, the system processing time optimized by the Kacem algorithm is more stable, and the stability value is less than the traditional production scheduling system. The processing time of the PSS based on GA optimization also shows a decreasing trend with the increase of iteration times. It can be seen that the processing time when the system reaches stability is only 18.7 seconds.

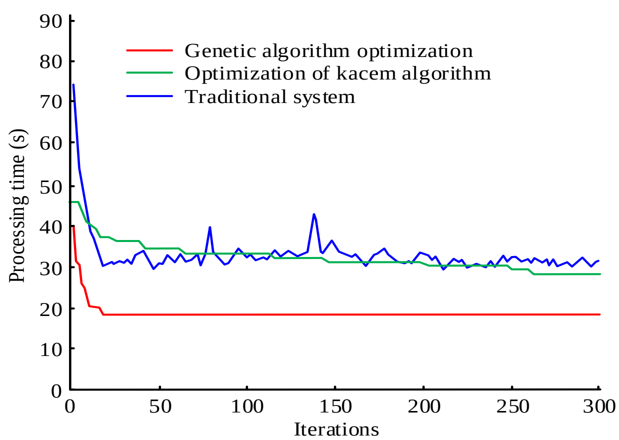


Figure 6. System production and processing time

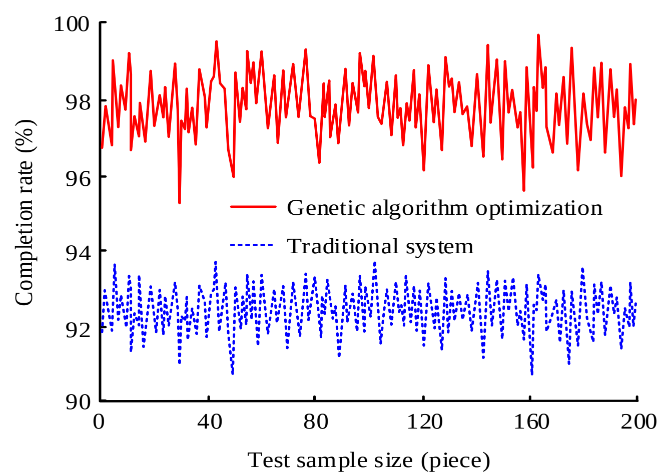


Figure 7. Analysis of production process completion rate

Secondly, the application effect of the production system based on GA optimization is analyzed by evaluating the production process completion rate of the PSS. The results are shown in Figure 7. In Figure 7, the differences between the production scheduling optimization system and the traditional production scheduling system are compared. The results show that the production process completion rate of the proposed production scheduling optimization system is more than 96%. With the continuous increase of the test workpieces, the completion rate can maintain a high degree for a long time. At the same time, the completion rate of the traditional PSS production process is below 94%, which is significantly lower than that of the optimization system. Therefore, the above results show that the proposed production scheduling optimization system can achieve effective processing of workpieces.

Finally, the processing time of the production scheduling optimization model in the workpiece processing is evaluated to prove the processing capacity of the system for different workpieces, as shown in Figure 8. Figure 8 shows the processing time of the optimized system and the traditional production scheduling system for the workpieces. The processing time of the traditional production scheduling system is more than 0.5s, while the processing time of the optimized system proposed in the study is less than 0.5s. From the change in processing time of the production scheduling optimization system, it can be seen that the minimum processing time of the optimization system is only 0.32s, while the minimum processing time of the traditional production scheduling system is 0.51s. Therefore, from the comparison between the optimization system and the traditional production scheduling system, the proposed PSS can improve the production completion rate while reducing the processing time of the workpiece, which has a high application value.

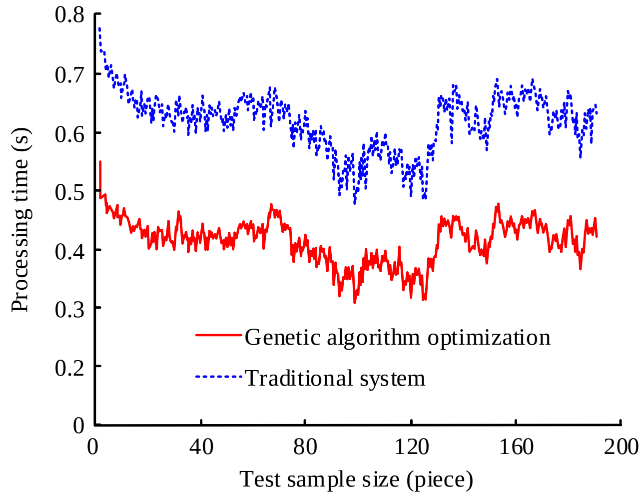


Figure 8. Processing time of workpiece processing

4.3 Green Manufacturing Evaluation of PSS

In the optimization of the PSS of the FMS, a strategy to minimize carbon emissions is proposed based on green manufacturing. For this purpose, the green manufacturing effect of the PSS is evaluated. The power change of the PSS is shown in Figure 9. In Figure 9, the power consumption between the cooling, processing and control equipment of the traditional production scheduling system and the optimized system is compared. In Figure 9 (a), the power of the cooling equipment in the traditional production scheduling system during operation exceeds 28 kW. The power of the processing equipment during operation reaches 26.8 kW. The working power of the control equipment reaches 15.2 kW. In Figure 9 (b), compared with the traditional production scheduling system, the maximum power of the optimized system cooling equipment after operation is 26.1 kW, the power of the processing equipment is only 19.8 kW, and the power of the control equipment is reduced to 12.1 kW. Comparing the working power between the two systems, it can be seen that the power of the optimized system is significantly reduced.

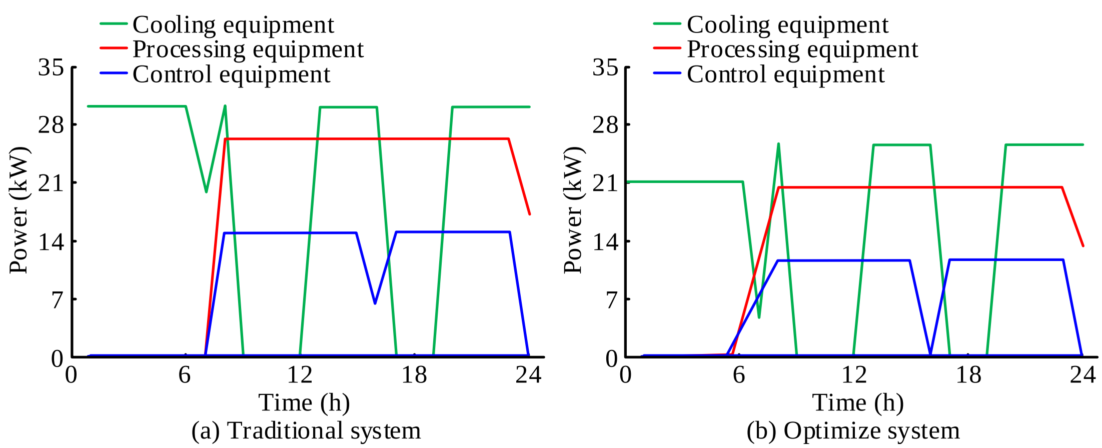


Figure 9. Power analysis of PSS

Finally, the cost consumption of the evaluation system, including production cost and carbon emission cost, are shown in Table 2. Table 2 shows that the cost consumption of the optimized system proposed in the study is lower than that of the traditional production scheduling system. From the analysis of cost consumption, it can be seen that the manufacturing, personnel and management costs of the optimization system are significantly lower than those of the traditional production scheduling system. The reason is that the optimization system has proposed a production scheduling optimization algorithm, thereby reducing cost consumption in production. In addition, as the optimization system introduces the strategy of minimizing carbon emissions, it is also significantly lower than the traditional production scheduling system in carbon emissions cost consumption. The above results show that the optimization system proposed in the study has low power in operation and low cost consumption. Therefore, it has the capacity of green production.

Table 2. Cost consumption of the system

Cost indicators		Traditional production scheduling system (USD)	Optimize system (USD)
Production costs	Manufacturing cost	5656.77	5152.33
	Personnel cost	5169.21	4948.17
	Administration cost	3042.15	2527.69
Carbon emission cost		698.74	432.83
Total cost		14566.87	13061.02

5. DISCUSSION

From this study, after the number of iterations reaches 20 times, the search accuracy average value of the Kacem algorithm grows to 84.26%, while the optimal solution of the data search accuracy rises to 91.65%. It stays in the stable accuracy range for a long time in the subsequent iterations of the calculation. As the number of iterations continues to increase, the data search accuracy of the genetic algorithm shows a growing trend. The accuracy average value of the genetic algorithm increases to 90.07% after the number of iterations reaches 15, while the optimal solution of the search accuracy reaches 96.62%. It shows that the genetic algorithm can achieve higher performance with a smaller number of iterations. The performance increase rate is much larger than that of the Kacem algorithm. The maximum computation time of the genetic algorithm operation is reduced to 320ms. The production process completion rate of the production scheduling optimization system based on the genetic algorithm also exceeds 96%. It shows that the model can make adjustments quickly according to the actual industrial production situation in the scheduling system. In the conventional system, the power of the cooling equipment is more than 28 kW, the power of the processing equipment reaches 26.8 kW, and the power of the control equipment reaches 15.2 kW. However, in the optimized system, the power of the cooling equipment reaches a maximum of 26.1 kW, the power of the processing equipment is 19.8 kW, and the power of the control equipment is reduced to 12.1 kW compared to the conventional system. It shows that the optimized scheduling system is able to save a lot of energy and bring some economic benefits to the company. In the traditional scheduling model, Bari and Karande found that the job processing time is generally regarded as a fixed time. This assumption may not be applicable to real industrial processes (Bari and Karande, 2023). Therefore, the team proposed a hybrid algorithmic model to target the job processing time in real industrial engineering.

The research team proposed that the DRCEC method is slightly better than the GA algorithm in terms of accuracy. However, due to the fact that the algorithm is a hybrid algorithm, it is much more complex and cumbersome than the GA algorithm. It also consumes a great deal of time to train the model in industrial processes. Therefore, in terms of overall performance, the GA algorithm is superior to the DRCEC method. Narayanan *et al*. found that the job shop scheduling problem is a major challenge in industrial production (Narayanan *et al*., 2022). Due to the increase in the number of jobs, the complexity of scheduling problems increases exponentially. It reduces the efficiency of the operations tremendously. Therefore, the research team solved the shop floor scheduling problem under static and dynamic conditions through heuristic methods. Although the proposed method can greatly improve resource utilization, it does not particularly improve green energy saving. The overall performance is slightly worse than the GA algorithm model. There are still shortcomings in this study. Genetic algorithms may lead to premature convergence in experiments. The production scheduling system proposed in the study does not take into account the impact of the shop floor environment. If the GA algorithm is improved, it can make the model more convincing.

6. CONCLUSION

The concept of green manufacturing has led to a shift in a large number of manufacturing industries towards low-carbon production. Therefore, how to achieve green production is the main direction of manufacturing development. Under the background of green manufacturing, the scheduling optimization strategy of FMS in the production shop is proposed. GA and carbon emission minimization methods are introduced in the study to achieve the optimization of production scheduling in the workshop. According to the results, compared with the Kacem algorithms, the production scheduling algorithm proposed in the study achieves the optimal data search accuracy of 96.62%. The maximum computing time is reduced to 320ms, and the production process completion rate of the production scheduling optimization system based on GA also exceeds 96%. Finally, the carbon emission test of the system shows that the power of the production scheduling optimization system is lower than that of the traditional production scheduling system. The maximum production power is only 19.8 kW. The carbon emission cost is also significantly lower than that of the traditional production scheduling system. The above results show that using GA to optimize the PSS is effective. The carbon emission minimization method can reduce the system operation power and reduce the carbon emission cost. However, the PSS proposed in the study does not consider the impact of the workshop environment. The external factors will be fully considered in the follow-up work to improve the scheduling capability of the system.

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