https://doi.org/10.31449/inf.v48i22.6369 Informatica **48** (2024) 85–98 **85**

Optimization of Production Scheduling in the Process Industry Using Decomposed Multi-Objective Evolutionary Algorithms

Haixia Chen
Institute of General Education, Zhengzhou Technical College, Zhengzhou 450000, China
E-mail: 15038310702@163.com

Keywords: production scheduling, decomposed multi-objective evolution, process industry, enterprise productiona

Received: June 5, 2024

The production scheduling problem in process industries is a complicated issue of complex multi-objective optimizing that has a significant impact on the production efficiency and economic benefits of enterprises. However, traditional scheduling methods often fail to meet the multi-objective optimization requirements in complex production environments. To improve the production efficiency and economic benefits of process industry enterprises, a production scheduling model for enterprises was constructed with production efficiency, product lead time, and production cutting frequency as optimization objectives. The study adopted a self-organizing mapping scheme to improve the decomposition of multi-objective evolution, and used the improved algorithm to solve the multi-objective optimization model. The results showed that when the optimization objectives were the max completing time and production switched number, the proposed method had a high convergence speed and Hypervolume value. The algorithm achieved convergence after 2100 evaluations with an Hypervolume value of approximately 0.302. The HypE algorithm achieved convergence after 2400 evaluations with a Hypervolume value of approximately 0.284. The algorithm also exhibited a high level of diversity, with an inverted generational distance value of approximately 0.672, which was higher than the other algorithms. The proposed algorithm demonstrates high convergence and diversity when solving the production scheduling model.

Povzetek: Razvit je razčlenjeni večkriterijski evolucijski algoritem za optimizacijo razporejanja proizvodnje, ki dosega hitro konvergenco (Hypervolume 0,302) in izboljšano raznolikost rešitev, kar povečuje učinkovitost procesne industrije.

1 Introduction

As the scale of papermaking enterprises increases, the computational time for solving scheduling problems grows exponentially, and it has been proven that non-deterministic polynomial (NP) hard can describe it [1]. Algorithms for solving scheduling problems often struggle to search the entire solution space for getting the globally optimum. Facing this situation, constraints can be set to eliminate infeasible solutions and decrease the feasible solution space size [2]. By adjusting the range of variable values and evaluating the impact of design constraints individually, the ability to solve the problem can be improved [3]. Papermaking enterprises aim to minimize the maximum completion time, total tardiness, and number of production switches, which are often conflicting objectives that require a proper balance. Additionally, production scheduling needs to consider processing sequences, equipment availability, and material constraints, making the scheduling problem complex [4]. Therefore, this study proposes a decomposed multi-objective evolution algorithm (MOE) based on self-organizing mapping, which utilizes prior knowledge of the problem to search for the approximate Pareto optimal solution set in a lower-dimensional space while maintaining diversity. The main contribution of this research is to provide effective production scheduling strategies for enterprises through the constructed model and algorithm, thereby improving production efficiency. It also aims giving a new research direction for papermaking enterprises. The structure of the study contains five components. In the first part, an overview is provided of the research conducted on the production scheduling problem and the multi-objective evolution problem of decomposition. In the second part, a decomposed MOE based on self-organization mapping is constructed and used to solve the production scheduling model. The third part analyzes the performance of the constructed algorithm and the model. The fourth part discusses the proposed algorithms and other current studies. The fifth part summarizes the performance of the constructed methods, analyzes the limitations of the research, and proposes future research directions.

2 Related works

Enterprise production scheduling is a highly complex problem, typically involving multiple constraints, objectives, and stochastic uncertainties. Therefore, many scholars have conducted research and analysis on production scheduling and decomposed multi-objective evolution methods. Jiang et al. summarized and analyzed the literature on production scheduling from the perspectives of centralized/distributed scheduling, distributed scheduling, and cloud manufacturing scheduling. Furthermore, considering the globalization of manufacturing and the changes in production patterns brought about by new technologies, the future challenges and trends in production scheduling were discussed, and predictions were made regarding the methods of production scheduling [5]. Negri et al. proposed a concept verification of a simple heuristic framework for robust scheduling applied to flow shop scheduling problems. The feasibility of this framework was demonstrated in a laboratory environment for flow shop applications [6]. Goli et al. studied the role of automated guided vehicles (AGVs) and human factors as essential components of automated systems in production scheduling problems. The study focused on unit formation and scheduling of parts with fuzzy processing times. The proposed objective functions included minimizing the manufacturing span of parts and inter-cell movements. Experiment outcomes displayed that the proposed one had good application in production scheduling problems [7]. Zhai et al. proposed three heuristic methods for job shop scheduling problems, simultaneously optimizing three objectives including manufacturing span. Maintenance activities were inserted into the solutions. For optimization, the blocks were moved as well as maintenance activities that were interested in the solution. The proposed algorithm solved different types of scheduling problems in the experimental results without any modifications [8].

In the research of decomposed multi-objective evolution, Zheng and Sun proposed a MOE based on two-stage hybrid learning. In the first stage, a genetic operator with adaptive scaling parameters was used. In the second stage, a K-means clustering method was employed to construct a mating pool for each subpopulation. Experiment outcomes displayed that this method outperformed other advanced ones for multi-objective evolution [9]. Zhao and his team proposed a multi-objective evolutionary optimization model for predicting river suspended sediment load. The model decomposed the measurement data based on lag time into several appropriate rotating components and a residual data, which were then used as input for analysis. The outcomes demonstrated that it evolved the prediction accuracy of the model [10]. Meghwani and Thakur focused on decomposition-based MOE using uniformly distributed weight vectors for decomposing MOE problems into multiple scalar optimization problems. They proposed an adaptive strategy and conducted experiments on benchmark problems with complex Pareto fronts. The results showed that this strategy helped improvement of solutions on the approximate Pareto front [11]. Zhang et al. released the multi-objective hybrid flow shop rescheduling and invented a decomposition-based cuckoo optimization MOE. This algorithm further optimized the solutions using a variable neighborhood descent strategy and employed a global update strategy. The superiority of this method in solving the problem was verified in the experimental results [12]. The study summarized the survey literature and compared inverted generational distance (IGD) with Hypervolume (HV) indicators of similar methods, as shown in Table 1.

Table 1: Summary of the survey results of the related work

Author	IGD	HV	Efficiency	Author	IGD	HV	Efficiency
Jiang et al.	0.541	0.264	24s	Zheng et al.	0.492	0.298	12s
Negri et al.	0.489	0.213	18s	Zhao et al.	0.526	0.267	23s
Goli et al.	0.503	0.225	32s	Meghwani et al.	0.548	0.257	28s
Zhai et al.	0.524	0.257	27s	Zhang et al.	0.534	0.233	28s

Based on the above analysis, research on MOE has become a hot topic. Although the aforementioned studies have made some progress, there are still limitations, such as the constraints of experimental validation, the complexity of the methods, and deviations from real-world situations. The construction of a scheduling optimization model is contingent upon the production scheduling situation of different enterprises. This model is designed to enhance the efficiency of enterprise production scheduling. Therefore, drawing on the experiences mentioned above, this study proposes a decomposed MOE based on self-organizing mapping, using the algorithm to solve the production scheduling model in the papermaking industry. The study utilizes this method to maintain population diversity in the decision space and find the approximate Pareto optimal solution set of the problem in a lower-dimensional space, which is a novel attempt in the field of MOE.

3 Production scheduling in the papermaking industry based on decomposed MOE

Improving production efficiency is the most effective way for process industry enterprises to enhance their own capabilities. The improvement of production efficiency involves optimizing the problems existing in the production process, and production scheduling is an important part of enterprise production. Therefore, research has been conducted to optimize the production scheduling in the papermaking industry. The research will be carried out in two aspects: the first part is the study of the production mode in the papermaking industry, and the second part is the construction of the production scheduling model for papermaking enterprises.

3.1 Construction of the production scheduling model for papermaking enterprises

Paper is an essential product in daily life, and there are many types of paper, including toilet paper, napkins, facial tissues, etc [13-14]. The production process in a paper mill is usually categorized as two stages [15]. The 1st processing stage is the production of basic materials for various paper products, and the second stage is the production of finished products such as rolls and tissues. Taking Company X as the analysis object, this company has a total of 6 production lines in the first processing stage, with each line being a BF paper machine distributed in 3 workshops. Each production line consists of a pulper, a refiner, and a paper machine. The distribution of the production lines in the production workshops of the company is shown in Figure 1.

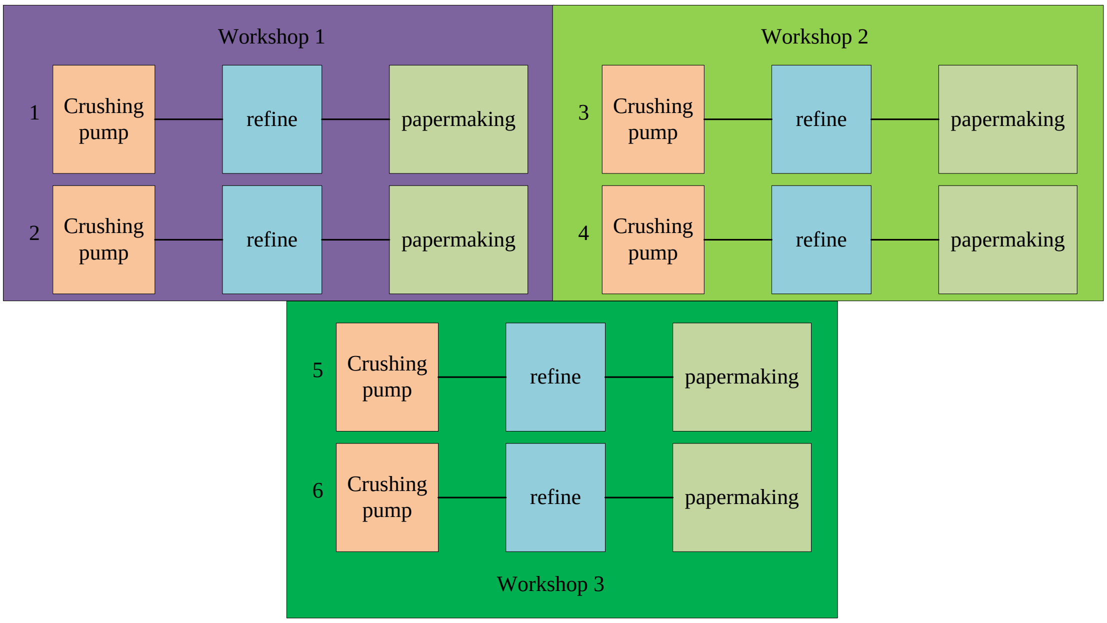


Figure 1: Distribution of the first stage processing production line

The key parameters of each line are similar. Based on the key parameters, the theoretical maximum daily production of the production line can be calculated using Equation (1).

$$r = 1440cdfqw \qquad (1)$$

In Equation (1), r represents the theoretical maximum daily production of the production line. c represents the theoretical speed. d represents the quantity. f represents the width. q represents the wrinkling rate, and w represents the production rate. In the second processing stage, there are more products. Taking the toilet paper production line of Company X as an example, there are a total of 7 toilet paper production lines distributed in three workshops. The toilet paper production line consists of three steps: rewinding, cutting, and packaging, as shown in Figure 2.

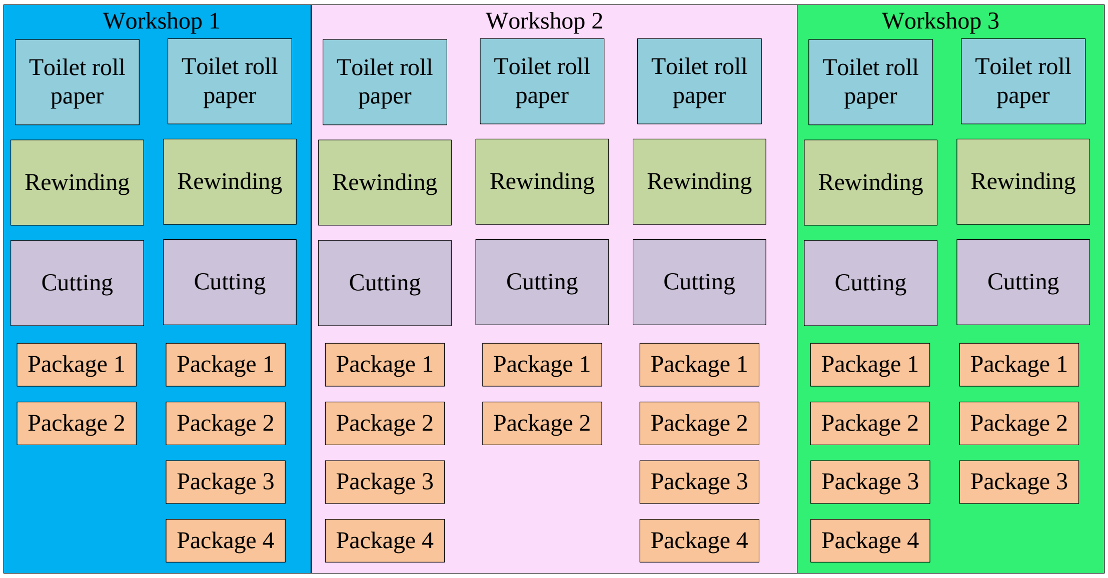


Figure 2: Distribution of production lines for the second stage of processing

The toilet paper production lines are composed of multiple devices in series and parallel. In the first stage, the raw materials obtained are rewound to form rewound bars, which are then cut to obtain paper rolls. Finally, the paper rolls are packaged to complete the production of toilet paper. The speed of the rewinding machine is based on the production process of the product, and the cutting machine can always match the speed of the rewinding machine, so as not to slow down the entire production line. However, the speed of the packaging machine is not always synchronized with the rewinding machine. If the speed of the packaging machine is higher than that of the rewinding machine, the speed of the production line is determined by the rewinding machine. Otherwise, it is determined by the packaging machine. The production speed of the rewinding machine can be calculated using Equation (2).

$$V_f = \frac{V_t ngd}{G} floor\left(\frac{D}{d}\right) \quad (2)$$

In Equation (2), V_f represents the actual production speed of the rewinding machine. V_t represents the theoretical production speed of the rewinding machine. n represents the number of layers of the rewound bar. g represents the mass of each roll. d represents the height of each roll, and G represents the mass of each layer. D represents the mass of each roll. The production speed of the toilet paper production line can be calculated using Equation (3).

$$V = \min\left(V_f, V_b\right) \quad (3)$$

In Equation (3), V represents the production speed of the toilet paper production line, and V_b represents the production speed of the packaging machine. Production scheduling is a crucial subfield of production management, which mainly maximize production efficiency and reduce production costs while meeting production demands. Production scheduling needs to consider various factors, including job sequencing, equipment availability, supply of raw materials and parts, and the impact of holidays or vacations. The effective management of production scheduling often necessitates the utilization of specialized software and programs. These facilitate the monitoring of production processes in real-time, the assessment of production status, the forecasting of future demands, and the timely responses and decisions that are required. The production scheduling process of an enterprise is shown in Figure 3.

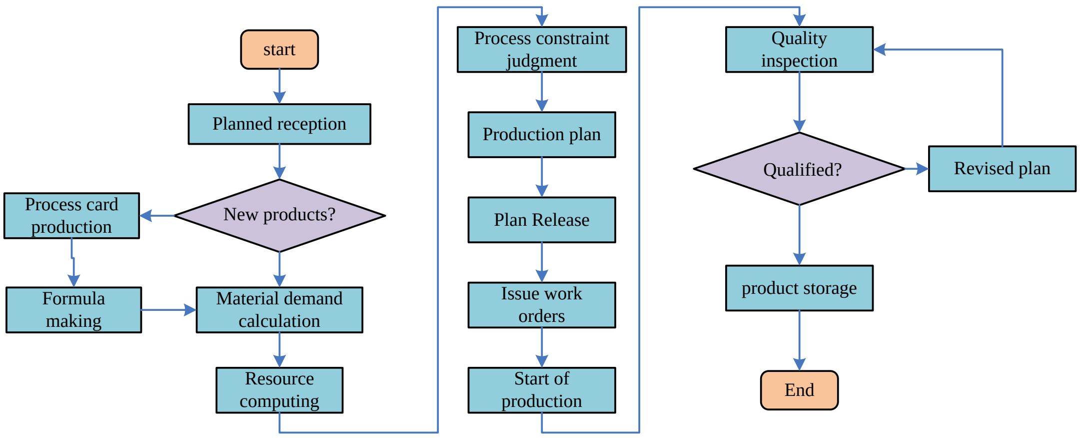


Figure 3: Enterprise production scheduling process

Optimizing production scheduling for an enterprise requires considering three factors: optimization objectives, objective constraints, and optimization algorithms. The performance indicators of production scheduling in an enterprise are the optimization objectives. Typically, performance indicators include maximum completion time, number of overdue tasks, and number of switches. Based on the above optimization objectives, the availability of equipment, raw materials, and production processes are considered as constraints for multi-objective optimization of production scheduling. Based on these conditions, a mathematical model for production scheduling in an enterprise is constructed. The model minimizes the maximum completion time, as shown in Equation (4).

$$\min\left(C_{i,j,2}\right) \tag{4}$$

In Equation (4), i represents the task identifier. j represents the production line identifier, and C represents the completion time. The minimization of the total number of overdue tasks is shown in Equation (5).

$$\min\left(\sum_{i=1}^{m_2}\sum_{i=1}^{m_{2,j}} f\left(C_{i,j,2}-D_i\right)\right) \tag{5}$$

In Equation (5), m_k represents the number of production lines for a single operation, and D_i represents the delivery time of the task i. The minimization of the number of production switches is shown in Equation (6).

$$\min\left(\sum_{k=1}^{2}\sum_{j=1}^{m_k}\sum_{i=2}^{m_{k,j}} h\left(P_{i-1,j,K},P_{i,j,k}\right)\right) \tag{6}$$

In Equation (6), h represents a parameter, and $p_{i,j,k}$ represents the product of the i-th task on the j-th production line. The calculation of task overdue is shown in Equation (7).

$$f\left(C_{i,j,2}-D_i\right)=\begin{cases}C_{i,j,2}-D_i & C_{i,j,2}>D_i\\ 0 & C_{i,j,2}\le D_i\end{cases} \tag{7}$$

The production switch for enterprise products is represented by Equation (8).

$$h\left(P_{i-1,j,K},P_{i,j,k}\right)=\begin{cases}1 & P_{i-1,j,K}\ne P_{i,j,k}\\ 0 & P_{i-1,j,K}=P_{i,j,k}\end{cases} \tag{8}$$

If $O_{i,j,k}$ is used to represent whether task i is produced on production line j, the value of $O_{i,j,k}$ should be set as binary. Equation (9) shows the representation.

$$0\, O_{i,j,k}=\begin{cases}0\\ 1\end{cases} \tag{9}$$

If $O_{i,j,k}$ is set to 0, it means that task i is not produced on production line j. If $O_{i,j,k}$ is set to 1, it means that task i is produced on production line j. The relationship between the number of tasks processed on each production line and $O_{i,j,k}$ can be represented by Equation (10).

$$\sum_{j=1}^{m_k}\sum_{i=1}^{n} O_{i,j,k}=n_{k,j} \tag{10}$$

In Equation (10), $n_{k,j}$ represents the number of processing tasks per production line. In enterprise production, the constraints on tasks can be represented by Equation (11).

$$\begin{cases} \sum_{i=1}^{m_k} O_{i,j,k} = 1 & \forall i \in 1,2,\dots n; \forall k \in 1,2 \\ \sum_{j=1}^{m_k} \sum_{i=1}^{n} O_{i,j,k} = n & \forall k \in 1,2 \end{cases} \tag{11}$$

In Equation (11), $\sum_{i=1}^{m_k} O_{i,j,k} = 1$ represents the constraint that task i can only be produced on one production line at a time. $\sum_{j=1}^{m_k} \sum_{i=1}^{n} O_{i,j,k} = n$ represents the requirement that all tasks need to be selected for production. During the production process, adjacent production tasks cannot be carried out simultaneously. The start time of the next task must be greater than the completion time of the previous task, as shown in Equation (12).

$$S_{i+1,j,k} < C_{i,j,k} \tag{12}$$

In Equation (12), $S_{i+1,j,k}$ represents the start time of task i+1. For adjacent operations in the same production line, there must be a time gap between them, as shown in Equation (13).

$$S_{i,j,k} - C_{i,j,k} \geq \alpha \tag{13}$$

In Equation (13), α represents the minimum time gap between adjacent operations. When constructing the mathematical model for production scheduling optimization, two constraints are set. The first constraint is the equipment availability constraint, as shown in Equation (14).

$$MS_{k,j} > C_{i,j,k} \tag{14}$$

In Equation (14), $MS_{k,j}$ represents the start time of equipment maintenance on production line j, and $MC_{k,j}$ represents the end time of equipment maintenance on production line j. The second constraint is the material constraint, as shown in Equation (15).

$$S_{i,j,k} > LB_i \tag{15}$$

In Equation (15), LB_i is the earliest starting time of the task i.

3.2 Solving the production scheduling model based on multi-objective decomposition evolution

The model constructed is an integer programming mixed with multi-objective. Common solution methods include decomposition MOE (MOEA/D) and non-dominated sorting genetic algorithm II (NSGA-II) [16]. MOEA/D is known for its fast convergence speed and simple algorithm structure, making it a suitable choice for solving the production scheduling optimization model [17]. MOEA/D's essential idea is the decomposition of the multi-objective optimization issue into multiple single-objective sub-problems using aggregation functions. These sub-problems have neighborhood relationships and are optimized collaboratively to find the Pareto approximate solution set for the optimizing problem. The MOEA/D flowchart is Figure 4.

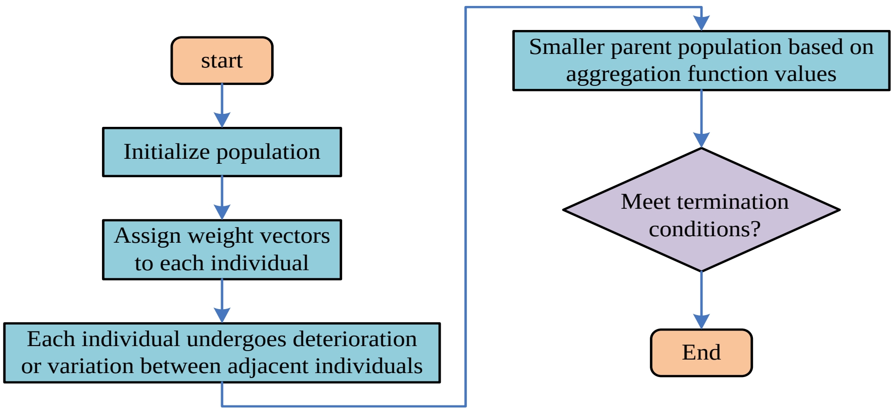


Figure 4: The MOEA/D algorithm process

The production scheduling optimization problem is a multi-dimensional multi-objective optimization problem that requires the use of aggregation functions to handle the optimization problem. The Chebyshev aggregation method can handle a wide range of aggregation problems, whether they are Pareto convex or Pareto concave problems. This method has high stability. The geometric interpretation of this method is shown in Figure 5 [18].

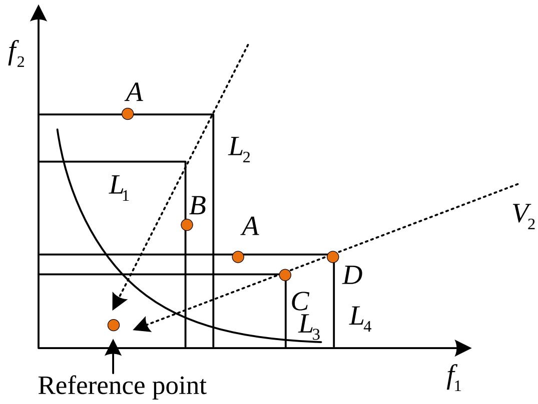


Figure 5: Geometric explanation of Chebyshev method

In the continuous Pareto front, the optimal solution of the Chebyshev sub-problem is the intersection point between the direction vector and the Pareto front. In the discontinuous Pareto front, it is possible for different sub-problems, each equipped with a distinct weight vector, to share the same Pareto optimal solution. This is because the direction vector may not intersect with the Pareto front. Unlike linear weight aggregation methods, the contour lines of the Chebyshev sub-problem have a right-angled sawtooth shape, which results in a smaller convergence acceptance region. When dealing with high-dimensional problems, the Chebyshev method can ensure the convergence of the population by reducing the convergence acceptance region. When using the MOEA/D to solve the optimization problem of the production scheduling model, it is necessary to construct the neighborhood relationship. This study investigates the use of self-organizing mapping methods to construct the neighborhood relationship in the MOEA/D. The structure of this method is shown in Figure 6.

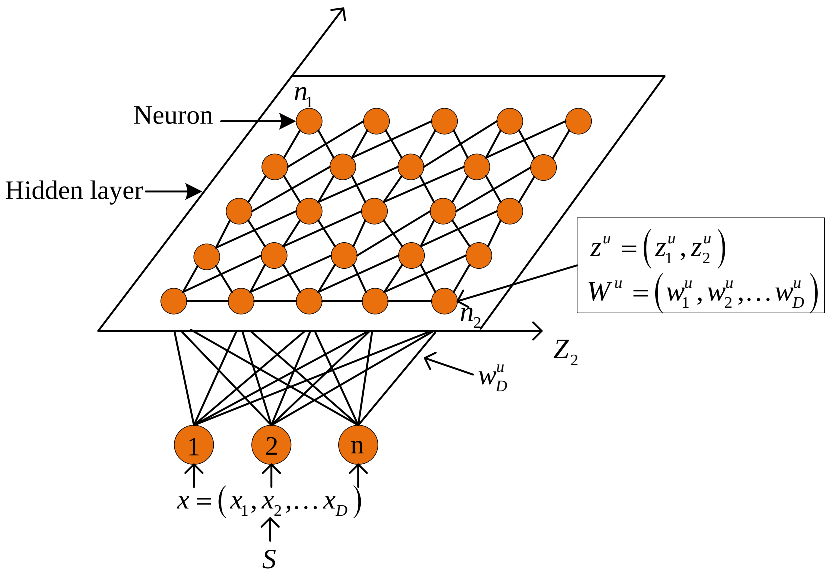


Figure 6: Self-organizing mapping method

Self-organizing mapping simulates the division of labor characteristics of neurons in different regions of the human brain, with each region exhibiting unique response features. It automatically classifies input patterns using an optimal reference vector set, where each reference vector represents the connection weight vector of an output unit. By treating the search space of the optimization problem as the input space of the self-organizing mapping, each candidate solution can be viewed as an input signal to the self-organizing mapping. Therefore, each neuron has its own topological structure, which includes the predefined position, predefined neighborhood, and input weights of the neuron. After the individual information is input into the network, the topological distance-invariant property of the self-organizing mapping can be used to construct the neighborhood of the candidate solution.

4 Experimental validation of the production scheduling model based on multi-objective decomposition evolution

In the previous sections, an overview of the production process of the papermaking company is provided. Moreover, a mathematical model for production scheduling optimization problem is constructed based on its production characteristics. The MOEA/D algorithm is then used to solve the production problem. To validate the feasibility of the model and the solution method, experiments are conducted in this chapter to validate the model.

4.1 Parameter settings

In the process of developing the production scheduling optimization model, the paper enterprise is selected as the subject of investigation. Accordingly, the production task of a paper enterprise is selected as the experimental design for the verification of the research model. The study uses 30 production scheduling tasks in Company X as experimental data. These production scheduling tasks include three types: 30, 60, and 90, with 10 tasks for each type. Each type of task includes 10 and 20 product types, with three production scheduling tasks for each product type. The specific details are shown in Table 2.

Table 2: Production scheduling tasks

Task	Production	Type	Task	Production	Type	Task	Production	Type
1	30	10	11	60	10	21	90	10
2	30	10	12	60	10	22	90	10
3	30	10	13	60	10	23	90	10
4	30	10	14	60	10	24	90	10
5	30	10	15	60	10	25	90	10
6	30	20	16	60	20	26	90	20
7	30	20	17	60	20	27	90	20
8	30	20	18	60	20	282	90	20
9	30	20	19	60	20	9	90	20
10	30	20	20	60	20	30	90	20

The MOEA/D algorithm proposed in the study is a type of multi-objective evolutionary algorithm. NSGA-II, strength Pareto evaluation algorithm (SPEA2), indicator based evolutionary algorithm (IBEA), and hypervolume based evolutionary algorithm (HypE) are all variants of genetic algorithms and can be used to solve multi-objective optimization problems. Therefore, in order to verify the effectiveness of the MOEA/D algorithm, the study compares the above algorithms with the MOEA/D algorithm. To maintain consistency of variables, all experiments are conducted using the same software on the same device. The device used in the study has a CPU of Celeron 3.60GHz, 8GB of memory, and MatLab2020b software. The setting of algorithm parameters directly affects algorithm performance. To reduce the impact of parameters on algorithm performance, the Adam optimizer is used to optimize the algorithm parameters. The initial population size of all algorithms is set to 100, and the termination condition for algorithm operation is the maximum number of function evaluations. The study set this number to 10000, and the crossover and mutation probabilities for all algorithms are shown in Table 3.

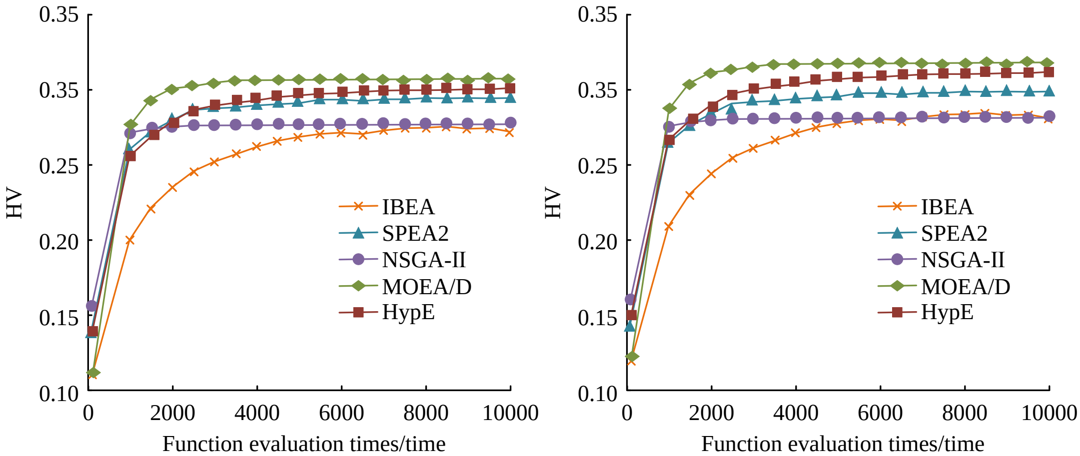
Table 3: Parameters

Algorithm name	Parameter settings	
	Crossover probability	mutation probability
NSGA-II	0.8	0.2
SPEA2	0.8	0.2
IBEA	0.8	0.2
HypE	0.8	0.2
MOEA/D	0.8	0.2

The evaluation criteria used are the HV and the IGD, which assess the convergence and diversity of the algorithms.

4.2 Analysis of optimization results for maximum completion time and production switch count

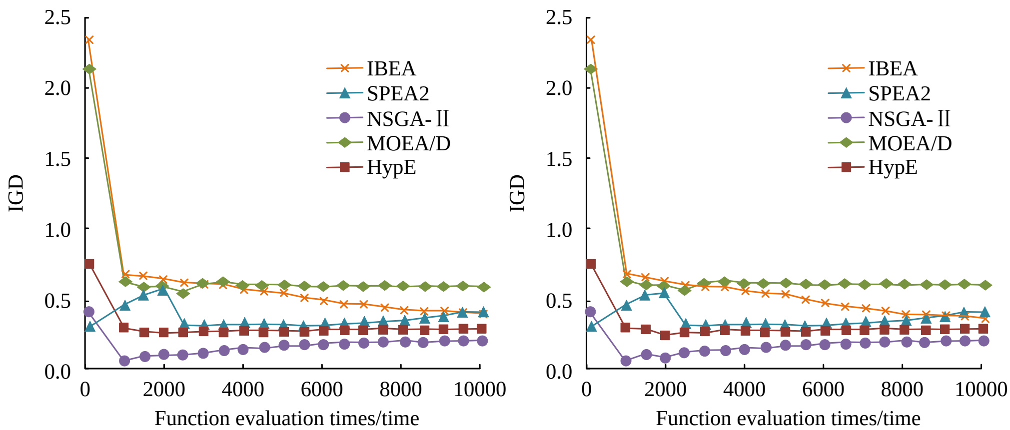
In actual production processes, minimizing the number of production switches reduces material waste and shortens the completion time. Therefore, the study analyzes above objectives' performance, which mainly contains maximum completion time and switch count optimization objectives for Task 1 and Task 11. The convergence results of the algorithms are shown in Figure 7.



(a) Convergence Comparison Results in Task 1 (b) Convergence Comparison Results in Task 11

Figure 7: Comparison of algorithm convergence

Figure 7(a) shows the convergence comparison results of the five algorithms for Task 1. It can be observed that at the initial state, the HypE algorithm has the highest HV value, around 0.158, while the MOEA/D and IBEA algorithms have the lowest HV value, around 0.183. As the function evaluation number increases, the HV values of all algorithms continue to increase. The IBEA algorithm converges at the 6000th evaluation, with an HV value of around 0.263. The NSGA-II algorithm converges at the 1000th evaluation, with an HV value of around 0.274. The SPEA2 algorithm converges at the 2400th evaluation, with an HV value of around 0.281. The HypE algorithm converges at the 2400th evaluation, with an HV value of around 0.284. The MOEA/D algorithm converges at the 2100th evaluation, with an HV value of around 0.302. Figure 7(b) shows the convergence comparison results of the five algorithms for Task 11. It can be observed that the order of the algorithms is similar to Figure 7(a). However, due to the increased number of products in this task, the HV values of each algorithm have increased to some extent. In conclusion, the MOEA/D has the second-fastest convergence speed after SPEA2, and it has the highest HV value after convergence. The diversity comparison outcomes of the five are displayed in Figure 8.



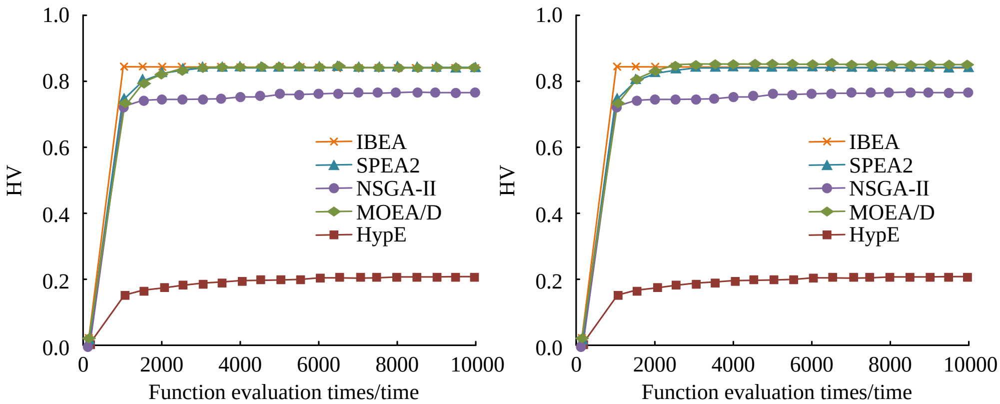
(a) Diversity Comparison Results in Task 1 (b) Diversity Comparison Results in Task 11

Figure 8: Diversity comparison results

Figure 8(a) displays the diversity comparison results of the five objectives for Task 1. The diversity of the MOEA/D algorithm decreases as the number of evaluations increases. It reaches its lowest point at the 1000th evaluation, with an IGD value of around 0.672. The diversity change of the IBEA is similar to that of the MOEA/D. However, its diversity reaches its lowest point after 8200 evaluations, with an IGD value of around 0.483. The diversity of the SPEA2 algorithm initially increases in the first 2000 evaluations, then starts to decrease and stabilize. The highest IGD value for this algorithm is 0.589, and the lowest is 0.287. Figure 8(b) displays the diversity comparing outcomes of the five for Task 11. It can be observed that the diversity changes of the algorithms are not significant compared to Figure 8(a). However, the IGD value of the IBEA algorithm shows a larger change, decreasing from around 0.483 to around 0.352.

4.3 Optimization results for maximum completion time and number of delayed tasks

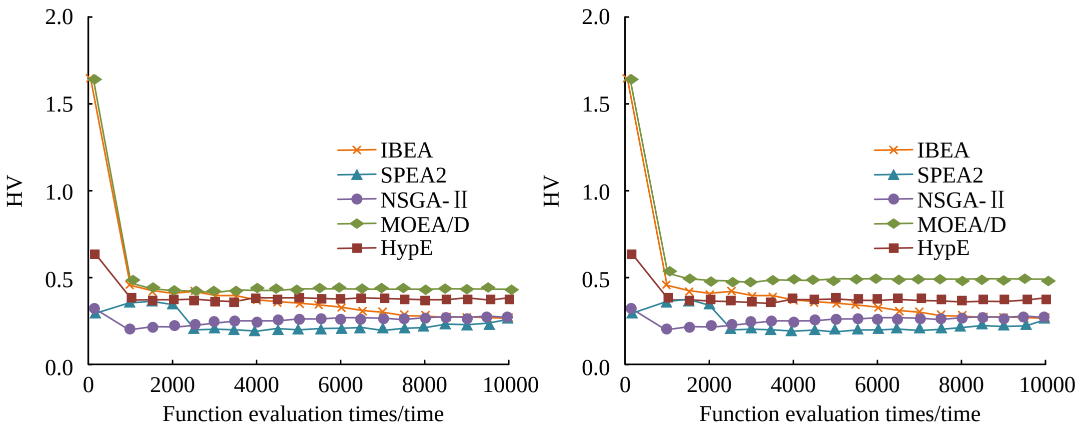
The more delayed tasks there are, the higher the cost of breach for the company and the lower the customer satisfaction. Therefore, the study also conducts experiments to optimize the maximum completion time and the number of delayed tasks. The convergence and diversity of the five algorithms are compared for Task 10 and Task 30. The convergence comparison results are shown in Figure 9.



(a) Convergence Comparison Results in Task 10 (b) Convergence Comparison Results in Task 20

Figure 9: Comparison of algorithm convergence

Figure 9(a) shows the convergence comparison of the five algorithms when optimizing for maximum completion time and the number of delayed tasks in Task 10. It can be observed that as the number of evaluations increases, the HV values of all algorithms increase. The HypE algorithm converges at the 2000th evaluation, with a converged HV value of around 0.184. The NSGA-II algorithm converges at the 1000th evaluation, with a converged HV value of around 0.726. The MOEA/D algorithm converges at the 2300th evaluation, with a converged HV value of around 0.823. Figure 9(b) shows the convergence comparison of the five algorithms when optimizing for maximum completion time and the number of delayed tasks in Task 20. Compared to Figure 9(a), the MOEA/D shows a slight increase in the converged HV value, while the other algorithms remain relatively unchanged. In conclusion, when there are a larger number of products and product types, the MOEA/D improves. Taking into account both convergence and diversity, the MOEA/D performs better when optimizing for maximum completion time and the number of delayed tasks. The diversity comparison results are shown in Figure 10.



(a) Diversity Comparison Results in Task 10 (b) Diversity Comparison Results in Task 20

Figure 10: Diversity comparison results

Figure 10(a) shows the diversity comparison of the five algorithms in terms of maximum completion time and number of overdue tasks as optimization objectives for Task 10. It can be observed that the diversity of the SPEA2 algorithm increases with the number of evaluations until approximately 2,000 evaluations, which is followed by a decrease to the lowest point at 2,500 evaluations and then a slight increase again. The lowest IGD value for the SPEA2 algorithm is around 0.273. On the other hand, the diversity of the other algorithms decreases as the number of evaluations increases. The diversity of the MOEA/D algorithm reaches its lowest point at 2000 evaluations, with an IGD value of 0.483. The diversity of the HypE algorithm reaches its lowest point at 1000 evaluations, with an IGD value of around 0.327. The diversity of the IBEA algorithm continuously decreases, while at 10000 evaluations, it has the lowest IGD value of around 0.251. Figure 10(b) shows the diversity comparison of the five algorithms in terms of maximum completion time and number of overdue tasks as optimization objectives for Task 20. The IGD value of the MOEA/D significantly increases, while the other algorithms remain relatively unchanged. In conclusion, the MOEA/D has the highest diversity. To further compare the robustness and efficiency of the analytical study design algorithms, the effects of different algorithms in practical production applications are compared. The results are shown in Table 4.

Table 4: Application effect of the study-designed model in the actual production

Algorithm	Enterprise 1			Enterprise 2		
	Number of delays (time)	Cutting frequency (time)	Production time (day)	Number of delays (time)	Cutting frequency (time)	Production time (day)
Blank	5	12	15	7	16	20
MOEA/D	0	4	9	0	7	13
HypE	2	7	12	3	12	17
NSGA-II	2	9	12	4	11	16

As illustrated in Table 4, the implementation of diverse multi-objective optimization models for the purpose of optimizing enterprise production scheduling has the potential to reduce the time required for enterprises to complete production tasks, as well as to minimize delays and enhance cutting times within the production process. When the MOEA / D algorithm is used, the number of delays in the production process can be reduced to 0 times. The number of cutting machine can also be reduced to 4 times, and the time spent to complete the production task is also reduced from 15 days to 9 days. The model can still maintain a good optimization effect in enterprise 2. The research design scheme is constructed with the physical manufacturing industry as the primary subject of investigation. It is predicated on the assumption that enterprise managers deploy enterprise production resources in an optimal state. However, in the actual implementation process, the staff may implement the low efficiency of the new program because of the operation habits. The assumptions made by the study will lead to the results of the model optimization theory to be greater than the actual implementation results in the firms.

5 Discussion

A multitude of factors influence the production tasks of enterprises, which in turn represent a central aspect of enterprise development. When engaged in production tasks, most of the resources and departments of the enterprise need to coordinate with each other to ensure the smooth progress of production tasks. Negri et al. demonstrated that developing a production scheduling framework tailored to the specific circumstances of a given company could lead to significant improvements in that company's profitability [6]. However, the enterprises investigated by the scholar are small and micro enterprises, which have insufficient applicability in large production enterprises. Therefore, the study focuses on the optimization of production scheduling in medium and large enterprises.

The experimental results showed that the multi-objective optimization model designed based on MOE/D algorithm could improve the IGD value to around 0.672 and reduce the HV value to 0.301 in actual solution performance. Zhao et al. used genetic algorithm to optimize and improve the decomposition multi-objective evolutionary algorithm, which could significantly improve the performance of multi-objective evolutionary algorithm in solving optimization models [10]. However, this method increased the computational complexity of the algorithm when solving the model, which reduced the computational efficiency of the model. The improved methods studied not only enhanced the performance of model solving, but also ensured the efficiency of model solving.

In conclusion, the current algorithms are inadequate for optimizing large enterprises due to insufficient algorithmic parameters, resulting in sub-optimal model solving efficiency and a poor optimization effect on the target. The algorithm designed in the study adopts a self-organizing mapping scheme to optimize the solving algorithm. Accordingly, the algorithm proposed in the study can effectively enhance the scheduling capability of enterprise resources when engaged in production tasks, thereby achieving the objective of reducing the time required for enterprise production tasks.

6 Conclusion

Production scheduling is one of the factors that affect the production efficiency of enterprises. Targeting at improving the production and economic benefits of process industry enterprises, a production scheduling model was constructed using a papermaking company as an example. The Chebyshev method was hired for decomposing the multi-objective optimizing into multiple single-objective sub-problems, and the self-organizing mapping method was used to classify them. Finally, the model was solved using MOEA/D. The results showed that when the maximum completion time and production switch count were used as optimization objectives, the MOEA/D algorithm converged after 2100 evaluations, and the HV value after convergence was around 0.302. The HypE algorithm converged after 2400 evaluations, with an HV value of around 0.284. The SPEA2 algorithm converged after 2400 evaluations, with an HV value of around 0.281. The lowest IGD value for the MOEA/D algorithm was around 0.672, the highest IGD value for the SPEA2 algorithm was 0.589, and the lowest IGD value for the IBEA algorithm was around 0.483. When the maximum completion time and number of overdue tasks were used as optimization objectives, the MOEA/D algorithm converged after 2300 evaluations, with an HV value of around 0.823. The successful integration of MOEA/D into the production scheduling model of process industry effectively addressed the multi-objective optimization problem through the combination of the Chebyshev method and self-organizing mapping. This provides a new solution for production scheduling in the process industry and helps improve production efficiency and economic benefits. In the future, further exploration will be conducted on the application of MOEA/D in complex production environments and how to better integrate practical production constraints into scheduling strategy design.

References

[1] J. Sassi, I. Alaya, P. Borne, and M. Tagina, "A decomposition-based artificial bee colony algorithm for the multi-objective flexible jobshop scheduling problem," Engineering Optimization, vol. 54, no. 3, pp. 524-538, 2022. https://doi.org/10.1080/0305215X.2021.1884243

[2] E. Jiang, L. Wang, and J. Wang, "Decomposition-based multi-objective optimization for energy-aware distributed hybrid flow shop scheduling with multiprocessor tasks," Tsinghua Science and Technology, vol. 26, no. 5, pp. 646-663, 2021. https://doi.org/10.26599/TST.2021.9010007

[3] B. Zhang, Q. Pan, L. Meng, X. Zhang, and X. Jiang, "A decomposition-based multi-objective evolutionary algorithm for hybrid flowshop rescheduling problem with consistent sublots," International Journal of Production Research, vol. 61, no. 3, pp. 1013-1038, 2023. https://doi.org/10.1080/00207543.2022.2093680

[4] B. Azevedo, R. Montanño-Vega, M. Varela, and A. Pereira, "Bio-inspired multi-objective algorithms applied on production scheduling problems," International Journal of Industrial Engineering Computations, vol. 14, no. 2, pp. 415-436, 2023. https://doi.org/10.5267/j.ijiec.2022.12.001

[5] Z. Jiang, S. Yuan, J. Ma, and Q. Wang, "The evolution of production scheduling from Industry 3.0 through Industry 4.0," International Journal of Production Research, vol. 60, no. 11, pp. 3534-3554, 2022. https://doi.org/10.1080/00207543.2021.1925772

[6] E. Negri, V. Pandhare, L. Cattaneo, J. Singh, M. Macchi, and J. Lee, "Field-synchronized Digital Twin framework for production scheduling with uncertainty," Journal of Intelligent Manufacturing, vol. 32, no. 4, pp. 1207-1228, 2021. https://doi.org/10.1007/s10845-020-01685-9

[7] A. Goli, E. B. Tirkolaee, and N. S. Aydın, "Fuzzy integrated cell formation and production scheduling considering automated guided vehicles and human factors," IEEE Transactions on Fuzzy Systems, vol. 29, no. 12, pp. 3686-3695, 2021. https://doi.org/10.1109/TFUZZ.2021.3053838

[8] S. Zhai, B. Gehring, G. Reinhart, "Enabling predictive maintenance integrated production scheduling by operation-specific health prognostics with generative deep learning," Journal of Manufacturing Systems, vol. 61, pp. 830-855, 2021. https://doi.org/10.1016/j.jmsy.2021.02.006

[9] W. Zheng, and J. Sun, "Two-stage hybrid learning-based multi-objective evolutionary algorithm based on objective space decomposition," Information Sciences, vol. 610, pp. 1163-1186, 2022. https://doi.org/10.1016/j.ins.2022.08.030

[10] N. Zhao, A. Ghaemi, C. Wu, S. Band, K. Chau, A. Zaguia, M. Mafarja, and A. Mosavi, "A decomposition and multi-objective evolutionary optimization model for suspended sediment load prediction in rivers," Engineering Applications of Computational Fluid Mechanics, vol. 15, no. 1, pp. 1811-1829, 2021. https://doi.org/10.1080/19942060.2021.1990133

[11] S. S. Meghwani, and M. Thakur, "Adaptively weighted decomposition based multi-objective

evolutionary algorithm," Applied Intelligence, vol. 51, pp. 3801-3823, 2021. https://doi.org/10.1007/s10489-020-01969-w
[12] B. Zhang, Q. Pan, L. Meng, X. Zhang, and X. Jiang, "A decomposition-based multi-objective evolutionary algorithm for hybrid flowshop rescheduling problem with consistent sublots," International Journal of Production Research, vol. 61, no. 3, pp. 1013-1038, 2023. https://doi.org/10.1080/00207543.2022.2093680
[13] M. Abbassi, A. Chaabani, N. Absi, and L. B. Said, "An elitist cooperative evolutionary bi-level multi-objective decomposition-based algorithm for sustainable supply chain," International Journal of Production Research, vol. 60, no. 23, pp. 7013-7032, 2022. https://doi.org/10.1080/00207543.2021.1999523
[14] X. Zheng, B. Han, and Z. Ni, "Tourism route recommendation based on a multi-objective evolutionary algorithm using two-stage decomposition and pareto layering," IEEE/CAA Journal of Automatica Sinica, vol. 10, no. 2, pp. 486-500, 2023. https://doi.org/10.1109/JAS.2023.123219
[15] Y. Fang, B. Luo, T. Zhao, D. He, and B. Jiang, "ST-SIGMA: Spatio-temporal semantics and interaction graph aggregation for multi-agent perception and trajectory forecasting," CAAI Transactions on Intelligence Technology, vol. 7, no. 4, pp. 744-757, 2022. https://doi.org/10.1049/cit2.12145
[16] J. Long, P. M. Pardalos, and C. Li, "Level-based multi-objective particle swarm optimizer for integrated production scheduling and vehicle routing decision with inventory holding, delivery, and tardiness costs," International Journal of Production Research, vol. 60, no. 11, pp. 3319-3338, 2022. https://doi.org/10.1080/00207543.2021.1919780
[17] L. Chen, W. Gan, H. Li, K. Cheng, D. Pan, L. Chen, and Z. Zhang, "Solving multi-objective optimization problem using cuckoo search algorithm based on decomposition," Applied Intelligence, vol. 51, no. 1, pp. 143-160, 2021. https://doi.org/10.1007/s10489-020-01816-y
[18] X. Wu, J. Peng, Z. Xie, N. Zhao, and S. Wu, "An improved multi-objective optimization algorithm for solving flexible job shop scheduling problem with variable batches," Journal of Systems Engineering and Electronics, vol. 32, no. 2, pp. 272-285, 2021. https://doi.org/10.23919/JSEE.2021.000024