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Many-Objective Production Scheduling Optimization Method for Aluminum Alloy Creep Forming Operation

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1. Introduction

Aluminum alloys are the most widely used non-ferrous metal structural materials in the industry. The large-scale structural components of aluminum alloy can satisfy the design and manufacturing requirements of light weight and high strength. So, they are widely used in the aerospace industry. Large-scale aluminum alloy components are the main structural materials in the aerospace industry, and promote the development of the aerospace industry. At present, creep aging forming technology has become an important manufacturing method for complex aerospace integral components [1].

Due to the increasingly customized product requirements of customers, the production characteristics of the aluminum alloy creep forming operation have changed to multiple varieties and small batches. Meanwhile, the aluminum alloy creep forming operation has unique production characteristics and process requirements, and the manufacturing system under the multi-variety and small-batch production mode becomes more complicated, resulting in complex production organization, low production efficiency, and high costs.

According to the production characteristics and actual production process of the aluminum alloy creep forming operation, the establishment of many-objective production scheduling model and the intelligent decision-making optimization method can reasonably allocate production resources, improve the production efficiency of manufacturing enterprises, reduce production costs, and enhance the level of intelligent manufacturing of enterprises [2]. Meanwhile, it is of great significance for developing the theory of production scheduling.

The intelligent production scheduling problem of the aluminum alloy creep forming operation is relatively complex. There are two main difficulties: 1 – there are many constraints and complex relationships in the aluminum alloy creep forming operation, and it is difficult to establish the production scheduling model that satisfies the actual production requirements of aluminum alloy aerospace components, 2 – the scheduling optimization problem of aluminum alloy creep forming operation has the characteristics of many-objective. In order to achieve high production efficiency, energy conservation, high rate of equipment utilization and low resource consumption in the manufacturing process, the production scheduling model with many scheduling objectives need to be established. At present, there is no effective scheduling optimization method to solve scheduling model of the production line.

At present, there is no research on the theory and application of the whole process production scheduling problem of aluminum alloy creep forming operation. The production scheduling model has not been established. The production scheduling problem of the production line cannot be optimized from a global perspective. For the scheduling of the single creep forming process, some scholars are currently conducting research. However, the existing filling method of the autoclave cannot effectively utilize the filling space of the autoclave, which reduces the production capacity of the autoclave.

In order to solve high-dimensional many-objective optimization problems, some optimization methods have been proposed, and can be roughly divided into three categories: dominance-based approaches, decomposition-based approaches, and the performance indicator-based approaches. Some many-objective optimization methods do not work well due to lack of selection pressure and population diversity. Qu, Zuo, Xiang, and Tao [3] established a high-dimensional flexible job shop scheduling model considering the total energy consumption, and proposed an improved electromagnetism-like mechanism algorithm to solve the model. In order to solve the job shop scheduling problem with limited workers, Li, He, and Cao [4] used a novel fitness evaluation mechanism (FEM) based on fuzzy correlation entropy (FCE) in the evolutionary algorithm. Meanwhile, in order to synchronically improve the convergence and diversity, a new environmental selection method is proposed. In order to solve a many-objective flexible job shop scheduling problem with transportation and assembly time, Sun, Zhang, Lu, and Zhang [5] designed a hybrid many-objective evolutionary algorithm (HMEA), and proposed a new non-dominated sorting method and tabu search method to better balance exploitation and exploration [6]. Liu, Chen, Zhan, Jeon, and Zhang [7] established a workshop scheduling model with five objectives, and proposed a multi-population co-evolutionary algorithm (MPMOGA) to optimize the solution. Each population optimizes one objective, and some improvement measures improve the optimization performance of the algorithm. Gong, Deng, Gong, and Huang [8] established a many-objective workshop nonlinear integer programming model based on worker index and green index. A new non-dominated ensemble fitness ranking algorithm (NEFRL) is designed for non-dominated solution sets. In NEFRL, a new fitness calculation method is proposed, which enhances the selection pressure of the algorithm [9]. In order to strengthen the convergence and diversity of high-dimensional many-objective optimization algorithms in the optimization process, Zhang, Li, Li, and Chen [10] proposed a many-objective evolutionary algorithm based on DPPs (determinantal point processes). Comparing with different types of optimization algorithms, it shows better computing performance. In order to improve the convergence of the NSGA-III ((Non-dominated Sorting Genetic Algorithm III) algorithm and enhance the selection pressure [11], Yuan, Xu, Wang, and Yao [12] introduced the decomposition-based idea of MOEA/D (Multi-objective Evolutionary Algorithm Based on Decomposition) into the sorting method of non-dominated solutions, and improved the environmental selection operation. Optimization performance has been improved. Decomposition-based evolutionary algorithms are being widely used. In order to better grasp the scalarizing methods applied in such methods, Rui, Zhang, and Tao [13] designed a simple yet effective method called Pareto adaptive scalarizing (PaS) approximation to approximate the optimal p value. Meanwhile, a PaS-based MOEA/D method is proposed. In order to improve the balance between convergence and diversity of evolutionary algorithms in the optimization process, Zhou, Zou, Yang, Zheng, and Pei [14] proposed niche-based and angle-based selection strategies, which effectively make up for the shortcomings of evolutionary algorithms. In order to effectively solve discrete optimization problems, Zhao, Zhang, Zheng, Zhang, and Zhang [15] proposed a decomposition-based ACO (Ant Colony Optimization) for discrete many-objective optimization. This method adopts an update strategy based on reinforcement learning, which effectively improves the convergence performance of the algorithm. In order to solve the constrained many-objective optimization problem and balance convergence and feasibility, Ming, Trivedi, Wang, Srinivasan, and Zhang [16] proposed a dual populations co-evolutionary algorithm-c-DPEA.

Evolutionary algorithms based on Pareto dominance have many shortcomings. With the increase of the number of objectives, the ability to distinguish the solution decreases, the strategy of maintaining the diversity is less effective, and the computational cost is high. In order to solve the many-objective whole-process production scheduling problem of the aluminum alloy creep aging forming components production line, the many-objective whole-process production scheduling model of the production line is established according to the production characteristics, technological process and production constraints. Meanwhile, multi-population coevolutionary optimization algorithm (MPCOA) is proposed to optimize the production scheduling model of the creep-forming production line. Based on the above methods, the many-objective whole-process production scheduling problem of the aluminum alloy creep forming components production line can be effectively solved.

The main contributions of this paper are as follows.

1. According to the production characteristics, technological process and production constraints, the many-objective production scheduling model of the aluminum alloy creep forming operation is established.

2. Multi-population coevolutionary optimization algorithm (MPCOA) is proposed. The MPCOA method uses three subpopulations for collaborative optimization. Multiple algorithms can effectively improve the optimization performance and collaborative search by integrating their respective advantages.

3. The many-objective production scheduling problem of the aluminum alloy creep forming operation is effectively solved. The solved scheduling scheme of the aluminum alloy creep forming operation satisfies the production requirements.

The rest of the paper is arranged as follows. Section 2 introduces the problem and model description. Section 3 introduces the MPCOA algorithm. Section 4 introduces the experimental results and discussion. Section 5 introduces the conclusions and the future work.

2. The Production Scheduling Model of Aluminum Alloy Creep Forming Operation

The production scheduling problem of aluminum alloy creep forming operation simultaneously optimizes five objective functions, namely the volume utilization rate of autoclave, completion time, delivery delay time, equipment idle time and the number of autoclave brackets. Let ~ respectively denote the five optimization objectives.

Nomenclature is as follows:

f_1 is the volume utilization rate of autoclave,
f_2 is completion time energy consumption,
f_3 is delay time machine load,
f_4 is equipment idle time,
f_5 is the number of autoclave brackets,
C_i is the completion time of the i-th workpiece,
a_{ij}^k is whether the operation O_{ij} is processed on equipment M_k,
t_{ij}^k is the processing time of operation O_{ij} on equipment M_k,
DD_i is the delivery date of the i-th workpiece,
n is the number of autoclave brackets.

Therefore, the whole-process production scheduling model of the creep aging forming production line including the five optimization objectives is established, and its specific definition is as follows:

$$min\, F = \left(-f_1, f_2, f_3, f_4, f_5\right). \tag{1}$$

Eq. (2) presents the volume utilization rate of autoclave. Improving the volume utilization rate of the autoclave can help to increase the production capacity of the autoclave equipment, achieve low resource consumption of the creep forming production line.

$$f_1 = \frac{\sum_{i=1}^{n} v_i}{n}, \tag{2}$$

where n is the total number of brackets in the autoclave filling plan, and v_i is the volume utilization rate of each bracket.

Eq. (3) presents the completion time. The completion time of creep forming line represents the processing time to complete all orders.

$$f_2 = \max\left(C_i \,\middle|\, i = 1, 2, 3 \cdots n\right), \tag{3}$$

where C_i represents the completion time of the last operation of the i-th workpiece.

Eq. (4) presents the delivery delay time. The reduction of delay time can improve customer satisfaction.

$$f_3 = \sum_{i=1}^{n} \max\left(C_i - DD_i, 0\right), \tag{4}$$

where DD_i represents the delivery date of workpiece i.

Eq. (5) presents the equipment idle time. The reduction of the idle time can reduce the production cost of the aluminum alloy creep forming components production line.

$$f_4 = \sum_{k=1}^{m} \left(T_k - \sum_{i=1}^{n} \sum_{j=1}^{q_i} a_{ij}^k \times t_{ij}^k \right), \tag{5}$$

where T_k is the stop time after the k-th equipment completes processing.

Eq. (6) presents the number of autoclave brackets. It can be beneficial to make full use of the remaining space on the autoclave bracket.

$$f_5 = n\,, \tag{6}$$

where n is the total number of brackets in the filling plan of autoclave.

The constraints of the whole-process production scheduling model are as follows. Eq. (7) indicates that there is no overlap between the mold positions of the two components placed on the autoclave bracket.

$$\max(x_{i1} - x_{j3}, x_{j1} - x_{i3}, y_{i2} - y_{j4}, y_{j2} - y_{i4}) \geq 0\,. \tag{7}$$

Eq. (8) indicates that the component position does not exceed the width of the autoclave bracket.

$$0 \leq x_{ik} \leq W\,. \tag{8}$$

Eq. (9) indicates that the longitudinal position of the component does not exceed the length of the autoclave bracket.

$$0 \leq y_{ik} \leq L\,. \tag{9}$$

Eq. (10) indicates that the vertical position of the component does not exceed the height of the autoclave support.

$$0 \leq z_{ik} \leq H\,. \tag{10}$$

Meanwhile, the layup station can only process one component at a time; the creep aging forming operation parameters of all components to be processed are known; Only components with the same or similar creep aging forming operation parameters can be placed in the same autoclave for creep aging forming operation; the number of components in the autoclave needs to be less than the number of vacuum nozzles and thermocouples.

3. Multi-Population Coevolutionary Optimization Algorithm (MPCOA)

The Multi-population coevolutionary optimization algorithm (MPCOA) is designed to optimize the whole-process production scheduling model of the aluminum alloy creep forming components production line. Different subpopulations can search different areas. Multi-populations collaborative search is conducive to maintaining the diversity of populations, and the sharing and fusion of search information can be achieved by the interaction between subpopulations.

3.1. Overview of the MPCOA method

The whole-process production scheduling model of the aluminum alloy creep forming operation is optimized and solved by the MPCOA method. According to the production characteristics of the aluminum alloy creep forming production line, a new encoding method needs to be adopted. Meanwhile, the decoding and genetic operators in the MPCOA method are designed for practical engineering problems, which can ensure that the MPCOA method can effectively solve the whole-process production scheduling model of aluminum alloy creep forming operation.

Firstly, the relevant parameters of the algorithm are initialized. A parent population with size N is generated. The initial population is divided into three independently evolved subpopulations S_1, S_2 and S_3. The three populations use different optimization methods respectively, and each type of optimization method is improved to better solve the whole-process production scheduling model of aluminum alloy creep forming operation. The first subpopulation uses the modified VAEA (vector angle-based evolutionary algorithm), the second subpopulation uses the modified decomposition-based evolutionary algorithm, and the third subpopulation uses the SDE-based SPEA2 (strength Pareto evolutionary algorithm) [17].

During the evolution process of the first subpopulation, the population S_1 obtains an offspring population Q_t by using genetic operators (selection, crossover, mutation). According to the probability of neighborhood search, local search is performed on the individual of the offspring population. The parent population and the offspring population are mixed to obtain population U_t. The combined population individuals are decoded to obtain the scheduling optimization objective value. Then, a vector angle-based environmental selection method is used to select the next generation from the population U_t.

During the evolution process of the second subpopulation, the optimization method uses the Uniformly Randomly (UR) and WS-Transformation to generate the weight vector of MOEA/D. The current minimum value of each optimization objective is calculated as the initial reference point. Two individuals are randomly selected from the individual's neighborhood. The offspring individuals are generated by genetic operators, and then the reference point is updated. The improved Tchebycheff aggregation function is used to update individuals in the neighborhood. Then every 10 iterations, the weight vector set is updated. Finally, a new population S_2' is obtained.

In the evolution process of the third subpopulation, the fitness of the individual population is calculated firstly, and the population S_3 is operated by using the genetic operator to obtain an offspring population with size N. A population with size $2N$ is obtained by mixing the parent and offspring populations. The fitness of the merged population is then calculated by using the SDE strategy.

Then every 10 iterations, an information exchange between the subpopulations is carried out to realize the collaborative search. Finally, the iteration termination condition is checked. If the above conditions are satisfied, the iteration is terminated, and the non-dominated solution set and the best compromise solution are output. Otherwise, the calculation process is continued. The flowchart of MPCOA is shown in Fig. 1.

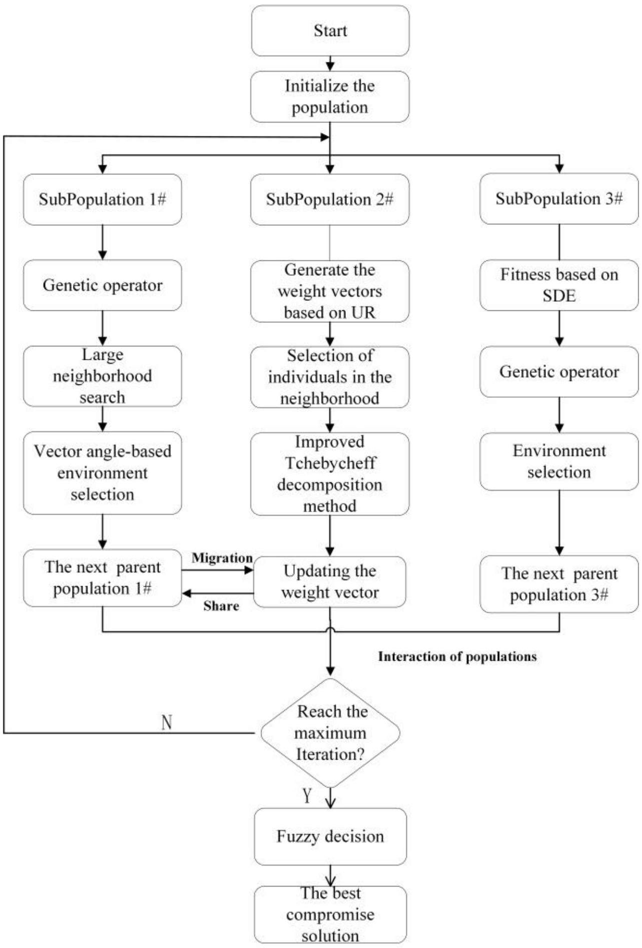

Fig. 1 The flowchart of MPCOA method.

3.2. Large neighborhood search

In order to speed up the convergence of the population and avoid local optima, the large neighborhood search is performed on the offspring individuals. A better solution is found by searching the neighborhood of the current solution.

In the large neighborhood search method, the neighborhood is implicitly defined by destroy and repair methods. The destroy method will destroy part of the current solution, and then the repair method will rebuild the destroyed solution. In order to destroy different part of the solution, the destroy method usually contains the element of randomness. Then, the neighborhood $N(x)$ of the solution x can be defined as follows: firstly, the solution x is destroyed by the destroy method, and then the solution x is reconstructed by the repair method. Finally, a series of solutions is obtained. The large neighborhood search strategy can expand the distribution space of the solution set. It can help to search finely, mine global information, and avoid local optimization.

The specific process of the large neighborhood search is as follows. Firstly, the number of genes p to be destroyed is set, and the original objective of individual i is recorded. In the destroy function, a sequence number containing all orders is randomly generated. The first p genes are recorded in the sequence number. Then the order numbers corresponding to the p genes are found in the current solution chromosome, and these order numbers are the removed individuals. The remaining chromosomal genes make up the remaining chromosomes.

The repair operation is performed on the remaining chromosomes. The removed genes are inserted into the remaining chromosomes. During the process of repair, the removed genes are placed on the remaining chromosomes. All individuals generated in this process are decoded. According to the concept of dominance relationship, the optimal insertion position of the first removed gene is determined in the remaining chromosomes, and then the remaining chromosomes are updated. All the removed genes are sequentially inserted into the remaining chromosomes in this way. Finally, a new solution is formed. According to the concept of dominance relationship, if the new solution can dominate the current solution, the current chromosome is replaced by the new solution chromosome. Otherwise, the current offspring chromosome remain unchanged.

3.3. The improved decomposition-based evolutionary algorithm

The Uniformly Randomly (UR) method is applied to generate the weight vector for MOEA/D [18-19].

Firstly, weight vectors are randomly generated uniformly, and these weight vectors form the weight set. Secondly, assuming that the number of optimization objectives is M, an m-dimensional identity matrix needs to be generated as a vector set. Thirdly, the Euclidean distance between the weight set and the vector set is calculated. The vector with the largest distance in the weight set is selected to replace the individual in the vector set, and this calculation process is repeated until the number of vectors in the vector set is N. After an initial weight vector set is obtained, WS-Transformation is used to transform Weight vector set [20]. Eq. (11) presents the formula of WS-Transformation.

$$\lambda_2 = WS(\lambda) = \left(\frac{\frac{1}{\lambda_1}}{\sum_{i=1}^{m} \frac{1}{\lambda_i}} \cdots \frac{\frac{1}{\lambda_m}}{\sum_{i=1}^{m} \frac{1}{\lambda_i}} \right), \tag{11}$$

where $\lambda = (\lambda_1 \cdots \lambda_m) \in R^m$.

The transformed weight vector set is proved to be able to optimize the discontinuous PF situation better, and can finally guarantee a relatively uniform non-dominated solution set. The decomposition-based multi-objective evolutionary algorithm aggregates each objective of the original multi-objective problem to obtain a single-objective optimization problem in a linear or nonlinear way, and uses the single-objective optimization method to obtain the Pareto optimal solution. When dealing with high-dimensional multi-objective optimization problems, the Tchebycheff method is used as a decomposition optimization method of aggregation functions. The Tchebycheff method limits the convergent receiving area, so it can better ensure the convergence of the population. However, for the uniformly distributed weight vector, the optimization results obtained by the Tchebycheff decomposition method have poor uniformity. This paper uses the improved Tchebycheff decomposition method [21].

Eq. (12) presents the improved Tchebycheff decomposition method.

$$\min g^{te}\left(x\middle|\lambda,z^{*}\right)=\max\left\{\frac{\left|f_j\left(x\right)-z_j^{*}\right|}{\lambda_j}\right\}. \tag{12}$$

The improved Tchebycheff decomposition method can not only solve non-convex problems, but also obtain uniformly distributed solutions.

3.4. Encoding and decoding method

In order to effectively optimize the whole-process production scheduling problem of the aluminum alloy creep forming components production line, the MPCOA method adopts the double-layer encoding method, as shown in Fig.2. The length of the chromosome is the number of workpieces. The first layer of encoding chromosomes represents the order in which the workpieces enter the autoclave. The second layer of encoding chromosomes is the placement direction of each workpiece. The placement direction of the workpieces determines whether the workpieces need to be rotated 90° when placed on the autoclave bracket. The proposed double-layer encoding method can effectively optimize the whole-process production scheduling problem of the aluminum alloy creep forming components production line.

8	4	3	6	7	1	2	5	9	10
0	1	1	0	0	1	0	1	1	0

Fig. 2 The double-layer encoding method

Decoding method can compute the encoding scheme into the workable production schedule. In the decoding process, the processing sequence of the workpieces that have been specified in the encoding chromosome and the orientation of each workpiece on the autoclave bracket are firstly determined. The creep forming operation is the bottleneck operation of the production line. The decoding operation firstly requires a clear autoclave filling plan for all workpieces to be processed. According to the order of all workpieces entering the autoclave and the orientation of each workpiece, the filling plan of the autoclave is arranged by using the remaining rectangle method. According to the filling plan of the autoclave, the number of the autoclave, the number of bracket layers, and the coordinates of the position can be determined. In the process of arranging production, the production of workpieces in each process is arranged according to the FCFS rule and FAM rule. Based on the above decoding method, the encoded chromosome can be converted into a production scheduling scheme for the aluminum alloy creep forming components production line.

4. Experiment Results and Analysis

This section demonstrates the feasibility and competitiveness of the proposed production scheduling model of the aluminum alloy creep forming operation and the proposed MPCOA method by the constructed industrial data set and actual production data.

4.1. Computational experiment of benchmarks

Since there is currently no standard benchmark case to test the production scheduling problem of aluminum alloy creep forming operation, in order to verify the proposed many-objective whole-process production scheduling model and Multi-population coevolutionary optimization algorithm (MPCOA), ten benchmark cases (Rbc01~Rbc10) are constructed, and the information of benchmark cases is shown in Table 1.

Table 1

The constructed benchmarks.

Benchmarks	Total number of component types	Total number of components
Rbc01	4	230
Rbc02	5	330
Rbc03	6	420
Rbc04	7	400
Rbc05	4	200
Rbc06	5	280
Rbc07	6	380
Rbc08	5	350
Rbc09	6	300
Rbc10	5	400

In order to prove the efficiency of the proposed MPCOA optimization method in solving the whole-process production scheduling model of the aluminum alloy creep-formed operation, we use RPD-NSGA-II, SPEA2+SDE, EFR-RR and PICEA-g as comparative optimization methods. In order to ensure the fairness of the comparison, the population size, crossover mutation method, and crossover mutation probability are all consistent, and each comparison method uses the mainstream autoclave BL (bottom-up left-justified) filling method. During the comparison, we use a fixed time as the iteration stopping criterion. Each benchmark case is calculated 5 times by the MPCOA optimization method, and each calculation iteration is 50 times. The average time of each case is calculated as the iteration stop time, as shown in Table 2.

Table 2

The average calculation time of each benchmark.

Benchmarks	Average time (s)
Rbc01	174.7802
Rbc02	262.6426
Rbc03	342.1754
Rbc04	325.068
Rbc05	145.3238
Rbc06	205.4072
Rbc07	313.043
Rbc08	285.258

The parameter settings of the MPCOA method are shown in Table 3. The *IGD* (Inverted Generational Distance) indicator and *HV* (Hypervolume) indicator are used to evaluate the performance of each optimization decision-making method.

Eq. (13) presents the calculation formulas of *IGD*.

$$IGD\left(P^*, P\right) = \frac{\sum_{x \in P^*} \min dis\left(x, P\right)}{\left|P^*\right|}, \tag{13}$$

where P^* represents non-dominated solution set and the solution set P represents Pareto Front.

Eq. (14) presents the calculation formulas of *HV*.

$$HV = \delta\left(\cup_{i=1}^{|S|} v_i\right), \tag{14}$$

where $|S|$ represents number of individuals in the non-dominated solution set.

In order to accurately judge the calculation effect of each scheduling optimization method, each decision-making optimization method is repeated 30 times in the process of solving benchmarks. Meanwhile, the calculated results were subjected to the Wilcoxon rank-sum test with a significance level of 0.05. The scheduling optimization experiment of the aluminum alloy creep forming operation in this section is calculated on the MatlabR2016b software.

The mean values of the *IGD* and *HV* indicators and the *P* values of the rank-sum test are shown in Table 4 and Table 5. In the experimental results, the indicator values that are significantly better than other algorithms are shown in bold. The MPCOA optimization method outperforms other algorithms in the *IGD* and *HV* indicator values of most test cases. According to the above experimental results, the efficiency and competitiveness of the whole-process production scheduling model of the aluminum alloy creep forming components production line and the MPCOA method are verified. The MPCOA method is not only feasible, but also has better optimization effect. The application of the MPCOA method can ensure that the aluminum alloy creep forming components production line can obtain satisfactory production schedule.

Table 3

Parameters setting.

Parameters	Value
Population size	100
Number of iterations	50
Mating probability	0.7
Mutation probability	0.1

In the Multi-population coevolutionary optimization algorithm, the global search performance of the multi-population co-evolutionary strategy is better, and the quality of the non-dominated solution set is improved. The MPCOA method includes three co-evolutionary populations. The three subpopulations use different optimization methods, and each type of optimization methods is improved to better solve the scheduling model of production line. The first subpopulation uses the improved VAEA method which integrates the large neighborhood search strategy to expand the distribution space of the solution set. It can help to search finely, mine global information, and avoid local optimization. The second subpopulation uses the improved MOEA/D method which can coordinate the convergence and diversity of the population and obtain a uniform solution set. The improved decomposition-based method uses an improved Tchebycheff function and adaptive update weight vector mechanism. The third subpopulation uses the SPEA method based on SDE. Its dominance relationship can reduce the difficulty of differentiation for solution set, increases the pressure of environmental selection, and improves convergence. Multiple algorithms can effectively improve the optimization performance by integrating their respective advantages, and different subpopulations can

Table 4

Statistical values of IGD

Problems	RPD-NSGA-II		SPEA2+SDE		PICEA-g		EFR-RR		MPCOA
	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value	Mean
Rbc01	77.8379	2.6695e-09	27.9922	0.8418	73.0327	2.9215e-09	36.4043	0.0038	28.4645
Rbc02	386.0097	3.6897e-11	305.2282	1.4643e-10	564.4506	3.0199e-11	340.2091	6.0658e-11	**48.9217**
Rbc03	64.9658	2.6099e-10	54.3940	4.5043e-11	564.4506	3.0199e-11	71.9549	3.3384e-11	**9.8658**
Rbc04	328.7601	3.6897e-11	253.7865	2.6099e-10	4.7495e+02	3.0199e-11	318.6348	6.0657e-11	**43.8647**
Rbc05	16.6238	5.5999e-07	64.4115	9.9186e-11	27.9543	1.0937e-10	11.8319	7.1988e-05	**8.1656**
Rbc06	1.8682e+02	5.5727e-10	1.6766e+02	1.2057e-10	3.1346e+02	3.0199e-11	1.8768e+02	1.6132e-10	**35.9393**
Rbc07	2.1387e+02	6.0658e-11	2.2894e+02	6.0658e-11	3.3234e+02	3.0199e-11	2.0885e+02	3.6897e-11	**26.2400**
Rbc08	1.6735e+02	1.1023e-08	1.6546e+02	2.9215e-09	2.9014e+02	4.5043e-11	1.8318e+02	2.8716e-10	**63.2410**
Rbc09	1.1776e+02	2.3715e-10	91.1889	3.3384e-11	1.7781e+02	3.0199e-11	1.1817e+02	3.0199e-11	**22.8652**
Rbc10	3.8769e+02	3.3384e-11	3.3497e+02	4.5043e-11	5.6691e+02	3.0199e-11	4.0374e+02	3.0199e-11	**83.7044**

Table 5

Statistical values of HV

Problems	RPD-NSGA-II		SPEA2+SDE		PICEA-g		EFR-RR		MPCOA
	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value	Mean
Rbc01	0.1218	3.6897e-11	0.1409	0.3112	0.1216	1.4643e-10	0.1311	5.5999e-07	0.1395
Rbc02	0.0593	3.0199e-11	0.0638	3.0199e-11	0.0487	3.0199e-11	0.0613	3.0199e-11	**0.0925**
Rbc03	0.0629	1.0937e-10	0.0700	4.5043e-11	0.0487	3.0199e-11	0.0585	3.3384e-11	**0.1245**
Rbc04	0.0575	3.0199e-11	0.0648	3.0199e-11	0.0439	3.0199e-11	0.0580	3.0199e-11	**0.1113**
Rbc05	0.1223	6.6955e-11	0.0146	5.4941e-11	0.1122	3.0196e-11	0.1283	2.4386e-09	**0.1417**
Rbc06	0.0252	3.0126e-10	0.0266	9.9127e-11	0.0019	6.4789e-12	0.0217	1.2028e-10	**0.0778**
Rbc07	0.0192	2.9155e-11	0.0172	2.9155e-11	0.0041	7.8787e-12	0.0203	3.0123e-11	**0.1013**
Rbc08	0.0656	1.2057e-10	0.0645	3.3384e-11	0.0414	3.0199e-11	0.0592	3.0199e-11	**0.1105**
Rbc09	0.0730	3.0199e-11	0.0813	3.0199e-11	0.0559	3.0199e-11	0.0730	3.0199e-11	**0.1195**
Rbc10	0.0309	3.0199e-11	0.0366	3.0199e-11	0.01114	2.9822e-11	0.0279	3.0199e-11	**0.0794**

search different regions. Multi-population cooperative search is beneficial to maintain the diversity of the population, and realize the sharing and integration of search information by the interaction between the subpopulations. Precocious convergence that can occur in a single population is avoided. The MPCOA algorithm can maintain high search efficiency. Under the premise of ensuring the diversity of the solution space, the co-evolution of the global search and the local search for the solution is realized.

The feasibility and efficiency of the MPCOA method are analyzed in detail with Rbc05 as an example. Fig. 4 depicts the evolution trajectory of the *HV* performance index measure along with the number of function evaluations when the five optimization methods solve the scheduling problem. The *HV* performance indexes of the five algorithms increase gradually with the increase of function evaluation times. In Fig. 5, the *HV* evolution curve of the MPCOA method is higher than that of other curves, and the above results indicate that *t* the MPCOA method has better evolutionary performance.

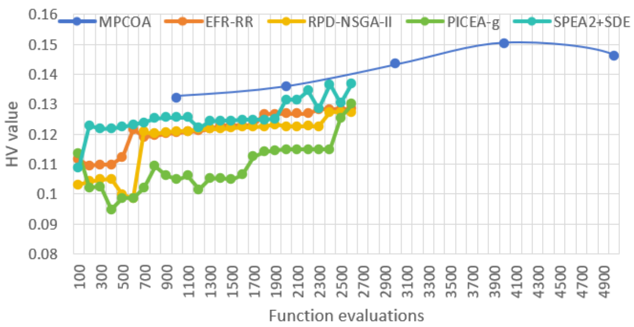

Fig. 4 The lid of launch vehicle fuel tank

Meanwhile, the MPCOA optimization method uses the autoclave filling method based on the remaining rectangle. The remaining rectangle filling method can make full use of the remaining space on the autoclave bracket, and improve the utilization rate of the autoclave. The MPCOA method can significantly optimize the filling sequence and orientation of components on the autoclave. Therefore, the MPCOA method can effectively solve the production scheduling problem of aluminum alloy creep forming operation.

5. Conclusions

In order to solve the many-objective production scheduling problem of aluminum alloy creep forming operation, the main work of this paper is concluded as follows:

1. According to the production characteristics, technological process and production constraints, the many-objective production scheduling model of the aluminum alloy creep forming operation is established.

2. Multi-population coevolutionary optimization algorithm, (MPCOA)is proposed. The MPCOA method uses three subpopulations for collaborative optimization. Multiple algorithms can effectively improve the optimization performance and collaborative search by integrating their respective advantages.

3. The many-objective production scheduling problem of the aluminum alloy creep forming operation is effectively solved. The solved scheduling scheme of the aluminum alloy creep forming operation satisfies the production requirements.

With the rapid development of the global manufacturing industry, in the future research, the traditional single-shop scheduling method cannot meet the needs of distributed manufacturing in modern manufacturing environment, which involves production units in multiple geographical locations and complex logistics networks. The scheduling coordination and optimization of the distributed manufacturing is more difficult. The production scheduling of distributed creep production line will be studied.

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MANY-OBJECTIVE PRODUCTION SCHEDULING METHOD FOR ALUMINUM ALLOY CREEP FORMING OPERATION

S u m m a r y

Due to the increasingly customized product requirements of customers, the production characteristics of the aluminum alloy creep forming operation have changed to multiple varieties and small batches. As a result, it has the problems of complex production organization, low production efficiency. As far as we know, this is the first time to study the production scheduling problem of the aluminum alloy creep forming operation. The production scheduling model is established. Multi-population coevolutionary optimization algorithm (MPCOA) is proposed. The MPCOA method uses three subpopulations for collaborative optimization. The sharing and integration of search information is realized through the interaction between subpopulations. For the optimization of the first subpopulation, an improved VAEA (vector angle-based evolutionary algorithm) which integrates the large neighborhood search is proposed. It can help to mine global information, and avoid local optimization. For the optimization of the second subpopulation, to get uniformly distributed solutions and improve the convergence, an improved decomposition-based method is proposed, which uses an improved Tchebycheff function and adaptive update weight vector mechanism. Computational experiments are performed by using industrial datasets and engineering production data. The competitiveness and superiority of the production scheduling model and the MPCOA method are demonstrated.

Keywords: aluminum alloy creep forming operation, multi-population coevolutionary optimization algorithm (MPCOA), many-objective optimization, production scheduling.

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