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Research on Many-Objective Scheduling Optimization Method for the Large-Scale Hybrid System

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1. Introduction

With the rapid growth of demand for high-performance alloy materials in the field of high-end equipment manufacturing, alloy smelting and casting production line is used as the core manufacturing unit. Its production scheduling efficiency directly determines the market competitiveness and resource utilization level of enterprises. In typical application scenarios such as aerospace and rail transit, alloy melting and casting process involves multi-stage coupling processes such as melting, refining, casting and heat treatment. These processes have the characteristics of high energy consumption, long cycle and strong coupling. Moreover, there are strict process constraints and time dependence between each process, which makes the production scheduling problem extremely complicated. These production characteristics have become an important bottleneck restricting the improvement of production efficiency. The purpose of this paper is to study the production scheduling problem of alloy casting production line and provide theoretical support and practical guidance for optimizing production scheduling.

At present, the production scheduling of alloy casting production line mainly relies on the traditional methods driven by experience, such as rule-based scheduling strategy and manual scheduling. Although these methods can meet the production demand to a certain extent, they often show problems such as low efficiency, serious waste of resources and slow response speed when facing the multi-variety, small-batch and highly customized production mode. In addition, with the rise of intelligent manufacturing technology, traditional scheduling methods are difficult to achieve efficient integration with advanced information systems (such as MES, ERP, etc.), which further limits the optimization space of production scheduling. Academia and industrial community have begun to explore scheduling methods based on optimization algorithms and intelligent technologies. For example, genetic algorithms, particle swarm optimization, deep reinforcement learning and other technologies are applied to solve complex production scheduling problems. These methods improve the flexibility and efficiency of scheduling, but they still face challenges such as high complexity of the model, high computational cost and unstable effect in practical application.

The production scheduling optimization of alloy smelting and casting production line presents significant challenges in intelligent manufacturing systems, with two primary complexities requiring resolution: 1. many-objective optimization problem. Production scheduling often requires trade-offs between multiple goals, such as minimizing production cycles, maximizing equipment utilization, reducing energy consumption, and reducing inventory. There is often a conflict between these goals. For example, improving equipment utilization may lead to increased energy consumption, while shortening production cycles may increase production costs. How to find the optimal balance point among multiple objectives is a difficult problem in production scheduling. 2. Complexity of process constraints. The production of alloy materials involves complex process constraints such as temperature control, time window limits, equipment compatibility, and so on. These constraints not only increase the complexity of scheduling problems, but also put forward higher requirements for the robustness and adaptability of scheduling algorithms.

To address high-dimensional many-objective optimization challenges, researchers have developed various computational methodologies. Niu et al. [1] studied the production scheduling problem of steelmaking continuous casting with uncertain process time, and obtained a more robust mathematical programming model by using indicators such as support set, mean value and covariance to describe uncertain process time. Huang et al. [2] studied integrated production scheduling with flexible flow shop as the object and multi-pass heterogeneous vehicle path planning in the soft time window, and proposed a hybrid collaboration framework based on hybrid algorithms. Yagmur et al. [3] proposed the meme algorithm and iterative local search method to solve the integrated production and distribution scheduling problem under the constraints of limited number of delivery vehicles and variable processing speed of processing machines. The optimization goal of this scheduling problem is to minimize the total cost. Sugianto et al. [4] proposed a rule-based heuristic particle swarm optimization algorithm to solve the integrated production and distribution scheduling problem of additive manufacturing and delivery distribution. The scheduling problem was optimized to minimize the total weighted time. Building upon foundational work in flow shop scheduling, Lee et al. [5] conducted a systematic review of existing methodologies while critically evaluating solution frameworks. Oujanas et al. [6] advanced the field through development of a mixed-integer linear programming (MILP) framework incorporating multi-constraint dynamics, with computational experiments demonstrating robust optimization capabilities. Advancing scheduling methodologies in textile manufacturing, Li et al. [7] established an evolutionary optimization framework leveraging genetic algorithms for spinning batch dyeing processes. Su et al. [8] pioneered a preference-conditional graph reinforcement learning architecture that employs parallel computation to approximate Pareto frontiers in multi-objective flexible job shop scheduling (MOFJSP). Extending beyond conventional approaches, Fan et al. [9] formulated a synergistic hybrid flow shop model with multiprocessor task coordination (HJSMT), subsequently engineering an enhanced NSGA-II variant for multi-objective resolution. Addressing human-machine collaborative dynamics in distributed systems, He et al. [10] developed a four-phase LSRF metaheuristic integrating: a – population initialization protocols, b – neighborhood search operators, c – solution space reconstruction mechanisms, and d – adaptive feedback control loops. Dai et al. [11] established a flexible job shop multi-objective scheduling model and proposed an improved NSGA-II algorithm. The artificial colony (ABC) algorithm is used for population initialization, and the simulated annealing (SA) algorithm is used for population screening. Zheng et al. [12] proposed a multi-objective optimization framework combining grouping technology to address the production scheduling problem of mixed-flow prefabricated parts. The non-dominant sorting genetic algorithm is introduced to solve this problem through adaptive population initialization strategy and population technique adjustment. Chang et al. [13-14] used group technology and planning theory to establish an optimization model for group mass production of PCS by minimizing production cost.

Xue et al. proposed dung beetle [15] and Vahedi-Nouri et al. [16] proposed a hybrid algorithm of multi-mesh Gray Wolf algorithm and NSGA-II for integrated scheduling in cloud manufacturing system. Álvarez-Gil et al. [17] proposed the multi-objective discrete firefly algorithm (MO-DFFA) to solve the job shop scheduling problem.

At present, there is no research on the theory and application of the whole process production scheduling problem of aluminum alloy casting production line. The theoretical research of production scheduling in the process industry is mainly concentrated in the steel and chemical industries [18, 19]. For example, Liu et al. [20] reviewed the research progress of the production scheduling problem in steelmaking and continuous casting, and proposed a multi-agent-based collaborative optimization method. There are few studies on the production scheduling problem of non-ferrous metal processing and manufacturing.

At present, there are still some problems in applying many-objective evolutionary algorithm to solve high-dimensional many-objective production scheduling problems of casting production line. High-dimensional many-objective production scheduling problems of casting production line usually involve complex constraints and large search space, resulting in a significant increase in computational costs. In high-dimensional target space, it becomes more difficult to maintain the diversity of the solution set, which tends to cause the solution set to be concentrated in the local region.

In order to solve the many-objective production scheduling problem of the melting and casting production line, firstly, a multi-objective production scheduling model of the whole process was established according to the production characteristics, process flow and production constraints. Meanwhile, a new high-dimensional multi-objective strong dominant optimization algorithm (SPEALNS) was proposed to solve the production scheduling model of high-performance alloy melting casting production line.

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

2. The Production Scheduling Model of Alloy Melting and Casting Production Line

The production scheduling problem of high performance casting and melting production line is considered to optimize four objective functions at the same time, namely, maximum completion time, delivery delay time, equipment utilization rate and adjustment time. $f_1 \sim f_4$ represents the four optimization objectives respectively. Therefore, the whole-process production scheduling model of high-performance alloy melting and casting production line containing four optimization objectives is established, which is specifically defined as follows:

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:

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

Eq. (2) presents the adjustment time of equipments f_1.

$$f_1 = \sum_{i=1}^{n} Tx_i + Tt_i \,, \tag{2}$$

where Tx_i and Tt_i represent the furnace washing time and mold adjustment time of the casting machine for the order i.

Eq. (3) presents the completion time f_2.

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

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

Eq. (4) presents the delivery delay time f_3.

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

where DD_i represents the delivery date of workpiece i.

Eq. (5) presents the equipment idle time f_4.

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

where T_k is the stop time after the k-th equipment completes processing, a_{ij}^k indicates whether the process O_{ij}^k is carried out on machine M_k, t_{ij}^k represents the processing time of the process O_{ij}^k on machine M_k.

During the scheduling process, there are some fundamental assumptions. 1. Static scheduling assumption: All orders (workpieces) are fully known before the scheduling process begins, and there are no subsequent urgent orders that are dynamically inserted. 2. No abnormal interference assumption: During the scheduling execution process, there are no sudden situations such as equipment failures, raw material shortages, or staff absences.

The constraints of multi-objective production scheduling problem of high performance alloy casting production line are as follows:

1. Process constraints.

Process constraint refers to the process specification that alloy needs to comply with in order to obtain qualified high-performance products in the production process. Eq. (6) indicates that there is a sequential constraint relationship between all processes of each workpiece, and the processing of the next process can only begin after the completion of the previous process

$$S_{\mathrm{ijk}} + T_{ijk} \le S_{ij+1p}\,. \tag{6}$$

2. Device constraints.

Equipment constraint refers to the operation specifications that all equipment in the high performance aluminum alloy melting casting line should comply with in order to ensure the efficient production of the production line. Eq. (7) represents that the same machine can only process one workpiece at the same time

$$\begin{aligned} &S_{ij} + M \times F_{ijk} \ge S_{jk} + T_{jk} \\ &S_{ij} + M \times \left(1 - F_{ijk}\right) \ge S_{jk} + T_{jk} \end{aligned}\,. \tag{7}$$

Eq. (8) represents that a workpiece can only be processed on one device at a time

$$\sum_{k=1}^{m} X_{ijk} = 1\,. \tag{8}$$

Eq. (9) represents a positive constraint

$$S_{ijk} \ge 0,\ T_{ijk} \ge 0,\ tr_{i,j-1,j} \ge 0\,. \tag{9}$$

3. The Strength Pareto Evolutionary Algorithm Based on Large Neighborhood Search (SPEALNS)

A new high-dimensional multi-objective optimization algorithm (SPEALNS) was proposed to solve the production scheduling model of high performance alloy casting production line. SPEALNS is based on the strength Pareto evolutionary algorithm (SPEA). Because of the production scheduling problem of aluminum alloy casting production line, a new coding method is needed.

3.1. Overview of the proposed method

Firstly, the coding method of the production scheduling problem is defined for the casting line. The parent population with size N was initialized. The fitness of the individual population was calculated. The genetic selection operation was carried out using the tournament method, and then the crossover and mutation genetic operators were used to operate the parent population to obtain an offspring population Q_t with size N. According to the neighborhood search probability, the individual neighborhood search of the offspring population is carried out. A population U_t with size $2N$ is obtained by mixing the parent population P_t with the offspring population Q_t. Then the fitness of the combined population U_t was calculated. In order to select N individuals from the population U_t, an environmental selection operation is required. First, individuals with fitness value less than 1 are selected. If the total number of individuals whose fitness value less than 1 is less than N, individuals with smaller fitness value of the combined population are entered into the next generation population. If the total number of individuals whose fitness less than 1 is greater than N, individuals need to be selected successively and deleted from the individuals whose fitness less than 1 according to the pruning process. This process continues to cycle until the maximum number of iterations is met. Finally, a set of scheduling solution set is obtained, and a high quality scheduling scheme is selected from the solution set by fuzzy decision method. The flowchart of SPEALNS is shown in Fig. 1.

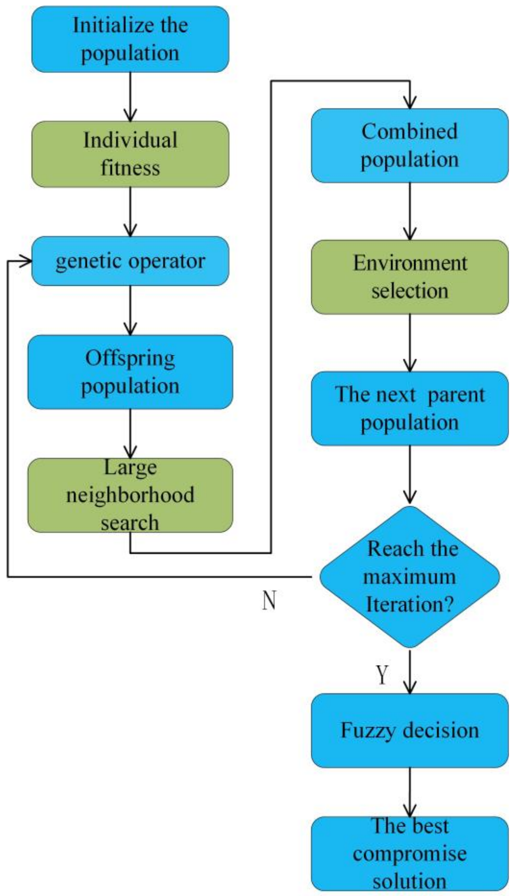

Fig. 1 The flowchart of SPEALNS method

3.2. Large neighborhood search

Large Neighborhood Search (LNS) is a kind of meta-heuristic algorithm based on destruction-repair mechanism. Its core idea is to achieve the balance between global exploration and local optimization by dynamically adjusting the neighborhood structure of the solution. In the destruction phase, adaptive rules are designed to remove some elements of the current solution. In the repair stage, the damaged part of the solution is completed into a feasible solution.

The algorithm steps of large neighborhood search are as follows. The number of genetic genes p to be stripped in deconstruction operation is set, and the baseline fitness evaluation value of initial individual i is obtained. In the execution phase of the destructor function, the random permutation sequence of the global task index is generated first. The first p genetic markers in this arrangement were extracted. Through the genetic coding mapping mechanism, the corresponding task identifiers in the current solution structure are located and the task set to be deconstructed is formed. The undeconstructed genetic fragments constitute the recombination base sequence.

The retained genetic sequences were reconstructed. In the recombination stage, the initially stripped genes are preferentially attempted to embed at different sites of the residual sequence, and a new gene combination is generated for each candidate location. The information was analyzed and the fitness was evaluated by non-inferior ranking rule. The optimal insertion site of the first gene in the remaining gene chain was determined, and then the basic sequence was reconstructed. All stripped genetic units are integrated according to the sequence of this iteration rule. Finally, a new candidate solution is constructed. Based on the Pareto dominance principle, if the new solution is superior to the existing solution in the target space, the new genetic code is used to replace the original structure. If no dominance is formed, the original genetic structure remains unchanged.

LNS implements deep exploration of solution space through cyclic destruction-repair operation. Its dynamic neighborhood characteristics can effectively escape the local optimal. Compared with traditional neighborhood search, large-scale destruction enhances global search, and intelligent repair mechanisms ensure refined and improved understanding.

3.3. The encoding and decoding method

To ensure that SPEALNS high-dimensional multi-objective optimization algorithm can effectively optimize and solve the production scheduling problem of high-performance alloy casting production line, the new encoding and decoding method of the SPEALNS is defined. One-dimensional real number encoding method is designed in this way. The random full arrangement method of job numbers is adopted for coding. Chromosomes represent the processing sequence of alloy batches. The number of chromosome sequences represents the serial number of alloy batches. The number of alloy batches to be processed is the length of chromosomes, and the code represents the processing priority of the workpiece.

If a chromosome sequence is [1 2 4 6 5 7 3 8 9 10], it means that there are 10 alloy batches that need to be processed, and the first alloy batch is processed in the first process, and then the next batches processed in sequence are 2. Fig. 2 shows the encoding method of the production scheduling problem in the melting and casting production line.

Decoding is to convert chromosomes into a scheduling scheme according to encoding information and encoding rules. The scheduling scheme is generally represented by Gantt diagram. Decoding is not a simple inverse opera-

1	2	4	6	5	7	3	8	9	10

Fig. 2 The encoding method

tion of encoding, and different decoding methods will produce different scheduling solutions. Because the casting process is the key process that determines the production capacity of the high-performance alloy melting and casting production line, this paper adopts the positive and negative hybrid decoding method. The reverse decoding method is adopted in the blocking continuous production stage. Firstly, the processing start and stop time of each batch is arranged from the casting machine to the melting furnace in accordance with the sequence in the code. In the discrete production stage of the melting and casting production line, the forward decoding method is used to arrange the production, where the decoding is carried out according to the process stage. After all batches have completed the processing start and end time of the current process, the scheduling arrangement of the next process is arranged. Based on the above decoding method, the encoding chromosome can be converted into the production scheduling scheme of high performance alloy casting production line.

3.4. Fitness calculation method

The fitness calculation method combines the Pareto dominance relationship and density information to ensure that the algorithm can converge to the Pareto frontier effectively and maintain the diversity of the population.

Fitness calculation is divided into two main parts. Strength represents the measure of an individual's dominance in a population. Density: Estimates the distribution density of an individual in the target space. The Density value estimates the distribution density of an individual in the target space.

Dominance relation: For each individual x in the population, Eq. (10) presents the number of other individuals that it dominates is counted

$$S(i)=\left|\left\{j \mid \ j\in P+Q\wedge i\succ j\right\}\right|. \tag{10}$$

Eq. (11) represents the strength value $R(x)$ of individual x

$$R(i)=\sum_{j\in Pop} S(j). \tag{11}$$

Eq. (12) represents density values $D(i)$. $D(i)$ are used to assess the distribution density of individuals in the target space to avoid the population falling into local areas. For each individual x, its distance to other individuals in the target space is calculated and the k-th nearest neighbor distance σ_i^k is found

$$D(i)=\frac{1}{\sigma_i^k+2}. \tag{12}$$

Eq. (13) represents the fitness value $F(i)$ of an individual. $F(i)$ is the weighted sum of the strength value and the density value

$$F(i) = R(i) + D(i). \tag{13}$$

To enhance the applicability of conventional Pareto-dominated MOEAs in high-dimensional multi-objective optimization, Li et al. engineered a shift-based density estimation (SDE) mechanism. Diverging from conventional approaches, this methodology incorporates dual-dimensional assessments of solution distribution patterns and convergence characteristics. The computational workflow involves: 1. pairwise displacement measurement between candidate solutions, 2. systematic aggregation of population-wide proximity metrics organized in ascending order, and, 3 iterative density quantification through adaptive distance thresholds. For minimization objectives, population density quantification is mathematically defined as: $D'(p,P) = D\left(dist(p,q_1'), dist(p,q_2')\dots dist(p,q_{N-1}')\right)$, where N represents the size of P, and $dist(p,q_i')$ represents the similarity between individual p and individual p_i'.

3.5. Genetic operator

In this paper, the two-point crossover method is selected for genetic crossover operation. Firstly, the two parent chromosomes are paired. If the random number is less than the crossover probability, the two paired parent chromosomes are crossed. Two intersections are arbitrarily selected on the coding chromosome, and then part of the gene segment is exchanged. The cross segment of parent 2 is placed before the encoding string of parent 1. Duplicate alloy batch numbers are checked from the starting gene, and the second alloy batch number appearing is deleted. In the same way, the cross segment of parent 1 is placed in front of the coding string of parent 2, and the genes of parent 2 chromosome are sequentially deleted. Finally, two progeny were formed. The two-point crossover method for the production scheduling problem of alloy casting production line is shown in Fig. 3.

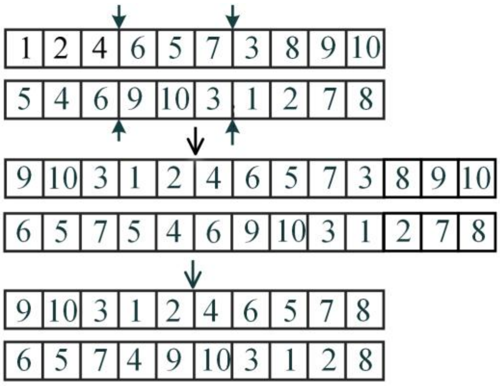

Fig. 3 The two-point crossover method

4. Experiment Results and Analysis

At present, there is no standard test example to test the production scheduling problem of alloy melting casting production line. Therefore, in order to verify the efficiency and feasibility of the proposed high-dimensional many-objective alloy melting casting production scheduling model and many-objective decision optimization method, six benchmark examples (Rz01~Rz06) were constructed. The feasibility and efficiency of the proposed whole-process production scheduling model and high-dimensional many-objective optimization decision-making method for high performance alloy casting production line were verified by the constructed industrial data set.

4.1. Computational experiment of benchmarks

Table 1 lists the number of orders for each benchmark calculation example. Table 2 lists the process parameters of all alloys used in the melting and casting data set.

Table 1

The constructed benchmarks

Benchmarks	The number of orders
RZ01	12
RZ 02	17
RZ 03	15
RZ 04	18
RZ 05	16
RZ 06	20

Six standardized test cases (Rz01-Rz06) were employed to comprehensively assess the operational viability and computational performance of the proposed whole-process production scheduling model and high-dimensional multi-objective optimization decision-making method for high-performance alloy casting production line. In order to more accurately evaluate the performance of each multi-objective scheduling optimization method in solving different benchmark examples, each optimization method was repeated for 30 times when solving each benchmark example. Wilcoxon rank sum test with significance level of 0.05 was performed for 30 performance indicators.

Table 2

The processing time

Operation	Type 1#	Type 2#
smelting	9 h	9 h
heat preservation	2 h	2 h
casting	2 h	2.5 h
soaking	19 h	0 h
Cooling operation	2.5 h	0 h
Machining operation	5 h	5 h

NSGA-II-RPD and MOEA/D were selected as comparison algorithms to prove the feasibility and superiority of SPEADLNS. Table 3 lists the parameters of the SPEADLNS algorithm.

IGD(Inverted Generational Distance) index was used to evaluate the performance of each optimization decision-making method. IGD represents the average distance from each reference point to the nearest solution, which can evaluate convergence and diversity at the same time. The smaller the IGD value, the better the comprehensive performance of the algorithm.

Eq. (14) presents the calculation formulas of IGD.

$$IGD\left(P^*, P\right) = \frac{\sum_{x \in P^*} min\, dis\left(x, P\right)}{\left|P^*\right|}, \tag{14}$$

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

Eq. (15) presents the calculation formulas of HV.

$$HV = \delta\left(\cup_{i=1}^{|S|} v_i\right), \tag{15}$$

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

Table 4 shows the average IGD value and the P-value of the rank sum test after each algorithm is run 30 times on all the benchmark instances. In the experimental results, values that are significantly better than other algorithms are shown in bold. The IGD index value of SPEALNS optimization method is better than other algorithms in all test cases. According to the above results, the efficiency and feasibility of the whole process production scheduling model and SPEALNS optimization decision-making method are verified for high performance alloy casting production line.

Table 3

Parameters setting

Parameters	Value
Population size	120
Number of iterations	50
Mating probability	0.75
Mutation probability	0.1
Destructive gene number	3

Table 4

Statistical values of IGD

Problems	NSGA-II-RPD		MOEA/D-THE		SPEALNS
	Mean	*p*-value	Mean	*p*-value	Mean
Rz01	28.2864	2.6099e-10	19.2511	1.1567e-07	**8.6814**
Rz02	29.5472	3.3519e-08	27.4417	2.5721e-07	**17.7158**
Rz03	29.4991	4.3106e-08	22.9083	2.2780e-05	**16.6754**
Rz04	50.9465	5.4617e-09	37.1772	6.3560e-05	**26.2069**
Rz05	22.4323	1.0232e-07	17.5071	3.5914e-05	**9.3528**
Rz06	47.0332	2.3884e-04	44.6391	6.5277e-08	**30.4315**

SPEALNS optimization method introduces the individual fitness calculation method in the process of multi-objective scheduling optimization. In order to distinguish individuals with the same original fitness value, a new method for calculating individual density value is introduced. This method combines a movement-based density estimation strategy. Different from other density estimation strategies, the SDE method includes individual distribution information and convergence information. These strategies improve the convergence and diversity of decision optimization methods. In order to accelerate population convergence and avoid local optimization, the SPEALNS method carries out large neighborhood search for progeny according to neighborhood search probability. The large neighborhood search method uses the destroy and repair functions to search the neighborhood of the current solution. This search strategy can find a better solution.

The feasibility of the whole process production scheduling model and SPEALNS decision optimization method are analyzed in detail by using Rz01 as an example.

We apply SPEALNS decision optimization method to solve the whole process production energy scheduling model, and obtain a set of non-dominated solutions. Fuzzy decision method is used to obtain the best compromise solution, which is the production scheduling scheme of Rz01 benchmark example.

Table 5

The best compromise solution

optimization method	completion time	delay time	the equipment idle time	the adjustment time of equipments
NSGA-II-RPD	**364**	**0**	883.5	44
MOEA/D-THE	366	**0**	877	42
SPEALNS	367	**0**	**849.5**	**39**

Table 5 shows the optimal compromise solutions of the three decision optimization methods. In the table 5, the best function values are shown in bold. As can be seen from Table 5, the optimal compromise solution obtained by SPEALNS is superior to other methods, only the completion time is slightly lower. The scheduling scheme obtained by SPEALNS can improve the utilization rate of equipment, reduce the adjustment time, reduce the production cost, and guide the production practice better. The results above prove the feasibility, effectiveness and superiority of the many-objective production scheduling model and SPEALNS method for high performance alloy casting production line. But, The key parameters involved in the proposed algorithm need to be manually tuned, resulting in poor robustness. There is no universal optimal value for the key parameters, and they need to be adjusted according to specific problems.

5. Conclusions

For the many-objective production scheduling problem of high performance aluminum alloy casting line, a multi-objective production scheduling model was established, and a new high-dimensional multi-objective optimization method (SPEALNS) was designed. The SPEALNS method was used to solve the production scheduling model. The encoding and decoding method and the corresponding genetic operator are designed in the optimization decision method, and the large neighborhood search strategy is added, which ensures the feasibility and efficiency of the optimization decision method. The feasibility and superiority of the whole process production scheduling model and optimization decision method were verified by using industrial data set in alloy casting production line.

For the future research, the production scheduling problem of the aluminum alloy casting production line studied in this paper belongs to static scheduling. During the actual production process of an intelligent factory, disturbance events (such as the insertion of urgent orders, equipment failures, etc.) often occur, which cause the initial scheduling plan to be disrupted. It is necessary to re-arrange the scheduling plan to ensure the stability and efficiency of the production system. Dynamic adjustment is more complex. It is necessary to study the high-dimensional many-objective dynamic scheduling problem to quickly and dynamically handle various disturbance events in the production process.

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RESEARCH ON MANY-OBJECTIVE SCHEDULING OPTIMIZATION METHOD FOR THE LARGE-SCALE HYBRID SYSTEM

S u m m a r y

For the many-objective collaborative optimization problem of high performance alloy casting manufacturing process, how to achieve high efficiency, low energy consumption and intelligent scheduling process is an urgent problem to be solved. Firstly, a multi-objective pro-duction scheduling model of the whole process was established according to the production characteristics, process flow and production constraints. Meanwhile, a new high-dimensional multi-objective strong dominant optimization algorithm was proposed to solve the production scheduling model of high-performance alloy melting casting production line. The proposed algorithm is designed by combining strong domination algorithm and large neighborhood search algorithm. The proposed algorithm method implements deep exploration of solution space through cyclic destruction-repair operation. Its dynamic neighborhood characteristics can effectively escape the local optimal. Based on the industrial data set of alloy casting production line, the performance of the model and the proposed algorithm are tested. Experimental results substantiate the effectiveness and comparative advantages of the many-objective scheduling model and the proposed algorithm method.

Keywords: the large-scale hybrid system, large neighborhood search, many-objective optimization, production scheduling.

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