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High-Dimensional Objective Flexible Sand Foundry Scheduling Under Green Manufacturing

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Abstract. With the increasing social awareness of green manufacturing, the sand casting, as one of the major production methods of carbon emission in the manufacturing, faces a major challenge in the coordination between production and sustainable development of green. In view of the carbon emission caused by electrical energy consumption in sand mold casting production, for the sake of achieving sustainable scheduling, a high-dimensional target flexible sand mold casting job shop scheduling model with carbon emission constraint is established, aiming to minimize the maximum completion time, minimize carbon emission, minimize the maximum machine load and minimize the processing cost. In order to solve the model, the PCA in machine learning is introduced into the optimization scheduling of high-dimensional objectives, and an improved PCA-NSGAII algorithm is adopted to reduce the dimension of the target. Finally, a practical scheduling problem is taken as an example to verify the feasibility of the algorithm. By comparison with traditional NSGAII DPSO PESAII algorithm, the effectiveness of the algorithm is demonstrated.

Keywords: Green manufacturing · Sand casting production · Optimization scheduling of high-dimensional objective · PCA-NSGAII algorithm

1 Introduction

With the continuous promotion of made in China 2025, the relationship between production and environment is increasingly inseparable, and the impact on the environment and effective utilization of resources in the production process have become the target factors that cannot be ignored [1]. As one of the main sources of carbon emission in the manufacturing industry [2], through appropriate scheduling schemes [1], sand casting can greatly reduce the carbon emission in the production process and realize the green manufacturing with energy saving and emission reduction [3]. The job-shop scheduling problem (JSP) is considered NP-hard [4], which can be described as the allocation of work on the machine [5]. The method of energy intensity decomposition is proposed to analyze carbon emission, and the calculation formula of carbon dioxide emission in the casting process is constructed [6]. Moreover a method for estimating and evaluating the boundary of carbon emission in casting production

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system is established, and the carbon emission in sand casting production process is calculated by carbon emission evaluation function [7]. A multiobjective particle swarm optimization algorithm based on preference for multiobjective flexible sand casting problem avoids the problem that decision makers are difficult to choose in many noninferior solutions [8]. Then, a hybrid fruit fly algorithm (HFFA) selects the Pareto frontier solution from existing solutions through fuzzy decision tools [9]. Actually aiming at the problem of high-dimensional objective optimization, PCA dominant mechanism based on weight coefficient is proposed, through the new selection mechanism to make up the disadvantage of Pareto sorting that the number of non-dominant solutions increases greatly due to the small selection pressure [10, 11].

2 Problem Description

2.1 Introduction of Sand Casting Process

Sand casting production is characterized by a small batch of individual pieces, and each casting has to go through a variety of complex technological processes from the material to the finished product. Process can be roughly classified into three major parts: modelling and core, melting and pouring, shake out and quality inspection. In addition, according to the machining features Process can be divided into two categories, machining and nonmachining of the technological process. Owing to the existence of nonmachining, sand casting job-shop scheduling problem is not entirely flexible job-shop scheduling problem (FJSP). In order to transform it into flexible sand casting job shop scheduling problem, the nonmachining process is virtualized into machine processing. Starting from the stage of pouring, the research on pouring, shake out, shot blasting, polishing and finishing is mainly carried out.

2.2 Process Buffer Time Interval

For the traditional FJSP, when a process of the job is completed, as long as the optional machine of next process is idle, the process can be processed. But in the field of sand casting, owing to its special processing technology characteristics, to meet the quality requirements of the castings, as soon as a process is complete, no matter whether the corresponding machine is idle or not, the next process can be processed after a certain process buffer the time interval.

2.3 Calculation Method of Carbon Emission in Processing

In the process of sand casting, the energy demand is different according to the process flow. For measuring the impact of electricity consumption on carbon emission, the standard coal conversion coefficient and carbon emission coefficient of electricity are used to convert the energy consumption value into carbon emission.

3 Mathematical Model

3.1 Shop Scheduling Model Analysis of Flexible Sand Casting

The classic FJSP can be described as: there are m machines and n job and each job has n_i processes. What is more, every process of each job can be processed on multiple machines, but the working procedure sequence of each process cannot be changed due to the limitation of technological process. Although each machine can process multiple operations, only one can be processed at a time. For the sake of studying the flexible sand casting shop scheduling model under the constraint of carbon emission, the following assumptions are made: (1) At the beginning of processing, each machine is idle. (2) Each machine can only process at most one process at any time. (3) Any process of any job can only be processed continuously in one machine. (4) The preparation time before the first process and the cleaning time of the last process are not considered. (5) Transport time between one process and the next is negligible. (6) The machine is only switched on and off once before starting and after finishing. The time can be ignored. By default, the machine is turned on before the job starts processing and always on during process. (7) The carbon emission mentioned here only considers the carbon generated by the power consumption of the processing equipment and dust removal equipment. The cost only considers the processing cost. (8) In the processing process, the worker's processing link is simulated as virtual process.

4 Notation Definition

(1) Because of the problem requires Table 1 to be some description of the notation used.

Table 1. Notation and description of FJSP Problem

Notation	Describe
n	casting total
m	total number of jobs
s	total dust removal equipment
n_i	total number of process for job i
i	serial number of job
j	serial number of process
h	serial number of processing equipment
c	serial number of dust removal equipment
O_{ij}	the process j of job i
C_{ijh}	the processing time of process O_{ij} on the machine h
T_{ijc}	the dust removal time of the process O_{ij} on the dust removal equipment c
J_{ij}	the buffer time interval between the process i and the process i + 1
y_{ijh}	the processing cost of process O_{ij} on the machine h
t_{ijh}	the finishing time of process O_{ij} on the machine h
P_h	rate operating power of the processing equipment h

(*continued*)

Table 1. (*continued*)

P_c	rate operating power of the dust removal equipment c
B	power standard coal conversion coefficient, 0.1229kgce/(KW · h)
EF	carbon emission coefficient of electric energy, 4.035 kgCO—2e/kgce
C_{max}	Maximum completion time
E	Maximum carbon emission
W_m	Maximum machine load
FC	The processing cost
A_{ij}	The starting time of process O_{ij}
B_{ij}	The ending time of process O_{ij}

(2) Decision variables

$$x_{ijh} = \begin{cases} 1, \ I_{ij} \ is \ processed \ on \ machine \ h \\ 0, \ I_{ij} \ is \ not \ processed \ on \ machine \ h \end{cases}$$

$$ST_{ijh} = \begin{cases} 1, \ process \ O_{ij} \ is \ the \ first \ process \ on \ machine \ h \\ max(t_{i'j'h}, t_{i(j-1)h} + j_{i(j-1)}), \\ process \ O_{i'j'} \ is \ the \ previous \ process \ of \ process \ O_{ij} \ on \ machine \ h \end{cases}$$

5 Building Model

For purpose of meeting the actual processing requirements, a mathematical model is established aiming at minimizing the maximum processing time, minimizing the maximum carbon emission, minimizing the maximum machine load and minimizing the minimum processing cost. The specific mathematical formula is as follows:

$$object \begin{cases} minC_{max} = min(\sum_{i=1}^{n}\sum_{j=1}^{n_i} C_{ijh} + \sum_{i=1}^{n}\sum_{j=1}^{n_i} J_{ij}) \\ minE = min[(\sum_{h=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n_i} P_h C_{ijh} + \sum_{c=1}^{s}\sum_{i=1}^{n}\sum_{j=1}^{n_i} P_c T_{ijc}) \times B \times EF] \\ minW_m = min(max\sum_{i=1}^{n}\sum_{j=1}^{n_i} C_{ijh} x_{ijh}) \\ minFC = min(\sum_{i=1}^{n}\sum_{j=1}^{n_i} y_{ijh}) \end{cases}$$

$B_{ij} + J_{ij} \le A_{ij+1}$, it limits the sequence of casting process. $\sum_{h=1}^{m} x_{ijh} = 1$, it limits each casting process to one machine.

$B_{ij} = A_{ij} + C_{ijh}$, the end time of the process j of the casting i is equal to the sum of its starting processing time and processing time, which restricts the continuous and uninterrupted processing of the process.

$ST_{ijh} \geq t_{i'j'h}$, It restricts each machine to only one process at any one time.

6 Design of Algorithm

6.1 The Introduction to the Improved NSGAII Algorithm

The general NSGAII algorithm mainly uses the Pareto algorithm to perform nondominated sorting for scheduling problems with multiobjective. However, as the goal increases to high-dimensional (four or more), solves the nonlinear scheduling model using the nondominated sorting optimization algorithm. The difficulty of selection increases, and the number of nondominated solutions increases exponentially, which greatly increases the difficulty of solving the problem. For the purpose of solving this problem, principal component analysis (PCA) algorithm is adopted for noise reduction of targets. Then PCA dominant mechanism is used to replace the nondominated sorting in population evolution, which increases the selection pressure of the algorithm on the nondominated solutions. On behalf of increasing the population diversity, the non-dominated solution set obtained from the first stage of population evolution and the parent solution set generated from the second stage are combined into a new population.

6.2 Population Initialization and Crossover Operations

The two-stage coding method is adopted, as the population is initialized, that is, the process sequencing and the machine selection [12]. The purpose of crossover and mutation in the population is to obtain more optimized chromosomes through some changes while retaining the characteristics of excellent individuals in the population. So as to improve the overall quality of the population, the selection strategy of the tournament is adopted. Select a part of chromosomes from the population for crossover and mutation, in which the process part is POX crossover [13]. Manipulating multiple genes on a pair of parent chromosomes enables the children chromosome to better inherit the gene of the parent chromosome. For example, a pair of process genes are Parent1 = [2,4,1,1,3,2,3,4] and Parent2 = [4,2,2,1,4,1,3,3]. Randomly select the processes 2 and 3 for crossover operation to obtain the child chromosomes Children = [2,4,1,4,3,2,3,1]. As in Fig. 1.

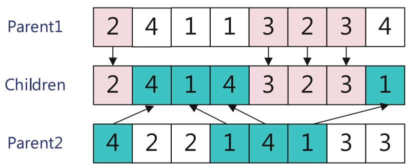

Fig. 1. Schematic diagram of POX intersection.

In addition, machine parts for the RPX crossover [14]. Randomly generate a matrix whose element size between [0, 1] and length is the same as the machine segment. Assuming that pf = 0.7, marking the machine code gene index of a member whose size is less than 0.7, the parent Parent1 is copied to the children, and delete the gene of the marked machine code. Then copy the machine gene in Parent2 to the children in the light of the correspondence between the marked gene and the process of Parent1. As in Fig. 2. The crossover weight pf is defined as follows:

$$pf = pf_{max} - \frac{pf_{max} - pf_{min}}{MaxIt} \times It$$

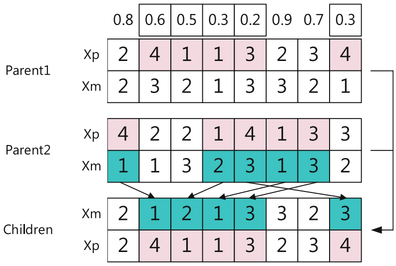

Fig. 2. Schematic diagram of RPX intersection.

6.3 PCA Dominant Mechanism

In the PCA analysis, in order to not change the target characteristics of the problem as much as possible, the discarding strategy is not adopted for the obtained redundant target vector. What is said here is that the noise reduction of the redundant target is to give it a weight according to its corresponding principal component, and then the redundant target will be fitted as a virtual target. If the target f_i is a nonredundant target determined by principal component N(N = 1,2…m), the weight of the target f_i is the proportion of the corresponding eigenvalue of the principal component N. Hence obtaining all the target weight coefficients w = $\{w_{1,}w_2 \ldots w_m\}$. The population evolution is sorted by PCA dominant mechanism, and the nondominated solutions are selected by difference selection operator. The specific formula is as follows:

$$f_i(a) - f_i(b) + \sum_{j=1, j \neq i}^{m} w_j(f_j(a) - f_j(b)) < 0,$$

a and b are two different individuals, f_i is any target, $f_i(a)$ is the value of target f_i of individual a. If this inequality is true, it means that individual a dominates individual b.

6.4 Algorithm Flow

See Table 2.

Table 2. Algorithm flow

Step1	Initial population
Step2	Population iteration yields the nondominated solution set P1
Step3	Perform PCA analysis on the target matrix of the nondominated solution set P1, and calculate the weight ratio w_i of the eigenvalue i
Step4	According to the dimensionality reduction principle of PCA, the ith principal component corresponding to the eigenvalue i can be obtained, and the nonredundant target f_i can be further obtained. Then, the weight of this target is w_i
Step5	Reinitialize the population and merge P1 and new population into one population Pt
	Determine whether the number of iterations reaches the upper limit. If yes, the algorithm ends. Otherwise, execute Step7
Step7	Selecting individuals from the population Pt with a certain probability for crossover and mutation operation, and combining the generated new individual and the original population into a new population
Step8	Put the optimal solution gbest into the population $P_{t+1,}$, which determined by nondominated sorting with the PCA dominant mechanism and execute Step6

7 Case Study

7.1 Case Description

The production data of a batch of castings from a foundry is analyzed. The relevant data includes 10 castings, each of which has 7 processes. The optional processing machine for each process is shown in Table 3. Table 4 shows the specific production data. In Table 5, the Power is the rated power of processing machines, the Power is the rated power of dust removal equipment corresponding to each processing machine, and the Cost is the processing cost per hour of machine processing. When calculating carbon emissions according to the standard, the carbon emission coefficient of electric energy is 4.035 $kgCO_2e/kgce$, and the power standard conversion coefficient is 0.1229 kgce/(kW·h).

Table 3. Process machine set of each process

	Operations						
	Pouring(I_1)	Shake out(I_2)	Initial shot blasting(I_3)	Polishing(I_4)	Rough cast(I_5)	Finishing(I_6)	Fine buffing(I_7)
M	[M_1–M_2]	[M_3–M_5]	[M_6–M_9]	[M_{10}–M_{13}]	[M_6–M_9]	[M_{14}, M_{16}]	[M_6–M_9]

Table 4. The specific production data

The casting	Process	Machine	Process time (h)	Buffer time interval (h)
Job1	I_1	[1,2]	[0.1,0.1]	15
	I_2	[3,4,5]	[1,1,1.5]	3
	I_3	[6,7,8,9]	[0.8,0.6,0.5,1]	1
	I_4	[10,11,12,13]	[1,1,1,0.5]	1.5
	I_5	[6,7,8,9]	[2,1,1,3]	1.5
	I_6	[14,15,16]	[4,4,3.5]	1
	I_7	[6,7,8,9]	[3,2,2,4]	15
Job2	I_1	[1,2]	[0.15,0.2]	20
	I_2	[3,4,5]	[1.8,1.5,2]	2.5
	I_3	[6,7,8,9]	[0.5,0.6,0.6,0.4]	1
	I_4	[10,11,12,13]	[0.5,0.5,0,5,1]	2
	I_5	[6,7,8,9]	[1,1,2,2.5]	1.5
	I_6	[14,15,16]	[3,3,3.5]	1.5
	I_7	[6,7,8,9]	[2,2,3,2.5]	20
Job3	I_1	[1,2]	[0.05,0.05]	10
	I_2	[3,4,5]	[0.5,0.5,0.8]	2.5
	I_3	[6,7,8,9]	[0.5,0.4,0.4,0.6]	0.5
	I_4	[10,11,12,13]	[0.5,0.5,0.5,0.5]	1
	I_5	[6,7,8,9]	[1.5,1.1,2]	1
	I_6	[14,15,16]	[3.5,4,3.5]	1
	I_7	[6,7,8,9]	[2.5,2,2,2.5]	10
Job4	I_1	[1,2]	[0.1,0.1]	16
	I_2	[3,4,5]	[1,1,0.8]	2
	I_3	[6,7,8,9]	[0.5,0.6,0.6,0.4]	0.5
	I_4	[10,11,12,13]	[1,2,1,1]	2
	I_5	[6,7,8,9]	[1.5,2,2,1]	1
	I_6	[14,15,16]	[3,3.5,4]	2
	I_7	[6,7,8,9]	[2,3,3,2]	16
Job5	I_1	[1,2]	[0.1,0.15]	17
	I_2	[3,4,5]	[1,1,1]	1.5
	I_3	[6,7,8,9]	[0.8,0.7,0.6,0.9]	0.5
	I_4	[10,11,12,13]	[1,2,2,2]	5
	I_5	[6,7,8,9]	[2.5,1.5,1,2]	1
	I_6	[14,15,16]	[2,2,2.5]	2
	I_7	[6,7,8,9]	[3.5,2.5,2,4]	17

Table 5. The Specific Production Data

M	M1	M2	M3	M4	M5	M6	M7	M8
Power	8	9	60	48	54	56	46	64
Power0	0	0	40	40	10	10	35	30
Cost	80	70	75	80	75	70	80	35
Power	42	5	6	4	4.5	0	0	0
Power0	0	0	0	0	0	0	0	0
Cost	40	40	30	35	45	50	30	35

8 Analysis of Results

An actual case is solved using this algorithm to verify the feasibility of the algorithm. And NSGAII DPSO PESAII as the comparison algorithm, the results of the four algorithms are compared as shown in Fig. 3. Set the same population size 50, maximum number of iterations 100, crossover probability 0.8, mutation probability 0.3, RPX parameter pfmax = 0.9, RPX parameter pfmin = 0.2. Considering the distribution of each target value, PCA-NSGAII algorithm is better than other algorithms. The result obtained by processing the data independently run by the four algorithms is shown in Table 6.

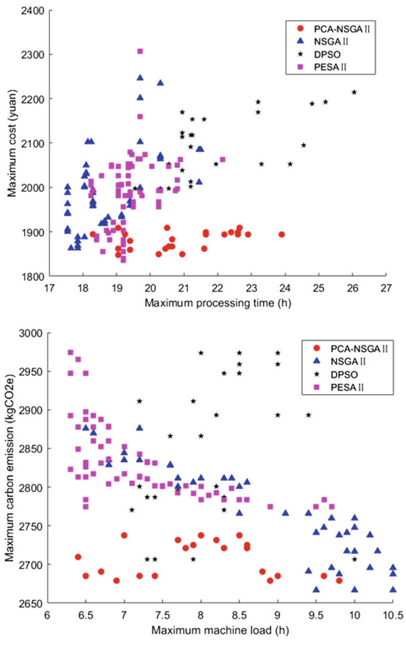

Fig. 3. Magnetization as a function of applied field.

Table 6. Four algorithms comparison results

Algorithms		PCA-NSGAII	NSGAII	DPSO	PESAII
Maximum machine load	⊿min	6.4	6.5	6.5	6.3
	⊿max	9.8	10.5	10	9.7
	⊿avg	8.164	9.121	7.845	7.375
Maximum carbon emission	⊿min	2678.987	2666.68	2706.615	2774.831
	⊿max	2737.585	2875.972	2973.528	2974.506
	⊿avg	2698.64	2752.615	2832.649	2825.996
Maximum processing time	⊿min	18.3	17.55	19.55	18.25
	⊿max	23.9	21.5	26.05	22.15
	⊿avg	20.675	18.339	21.23233	19.351
Maximum cost	⊿min	1848	1863	1997.5	1882
	⊿max	1909	2246	2214.5	2306.5
	⊿avg	1876.633	1971.66	2069.227	2007.32

It can be seen from the minimum ⊿min and maximum ⊿max and the mean value ⊿avg of the four targets that PCA-NSGAII significantly optimizes the carbon emission and processing cost while maintaining the processing time and the maximum machine load at a general level. Considering four goals in general, the PCA-NSGAII algorithm is better than other algorithms.

9 Conclusion

Under the background of sand casting for high-dimensional objective flexible job-shop scheduling problem, adopting the PCA algorithm instead of the traditional nondominated sorting algorithm effectively solves the problem that the number of the non-dominated solutions increases sharply, when the selection pressure decreases due to the increase of targets. However, at the same time, the running time also increases. In subsequent studies, the algorithm of taboo search and simulated annealing can be considered to improve the local search ability of the algorithm and the selection ability of the algorithm. In the actual production process, there are often multiple objectives to meet the needs of various aspects. For high-dimensional target optimization problems, more effective fitness value calculation methods can be explored. For the concept of green development, constraints such as noise and dust can be added to the model.

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