Preprints, 10th IFAC International Symposium on
Advanced Control of Chemical Processes
Shenyang, Liaoning, China, July 25-27, 2018

A Scheduling Method Based on NSGA2 for Steelmaking and Continuous Casting Production Process

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Abstract: In this paper a new non-dominated sorting genetic algorithm with elite strategy (NSGA2) based production scheduling method is proposed for complex steelmaking and continuous casting production process which is consisted of multiple refining ways. At first, the multi-objective optimization scheduling model is established according to production process and schedule requirement. And then NSGA2 is used to solve the scheduling model. There are multiple Pareto non-inferior solutions from the solving phase, and decision maker may select one of solutions based on own preference, while it is not the most optimal. To fix this problem, the optimal decision making method is put forward, combining the fuzzy membership degree and the variance weighting. Simulation experiments are carried out with the actual industry production data, which shows that the proposed method is practical for industry production.

Keywords: Steelmaking and continuous casting, production scheduling, multi-objective optimization, the non-dominated sorting genetic algorithm with elitist strategy, membership degree, variance weighting.

1. INTRODUCTION

Steelmaking and continuous casting is the most important process in the whole process of steel production. The formulation of its production scheduling scheme is the key to the stability of steel production and the smooth flow of logistics.

The traditional schedule scheme of steelmaking and continuous casting in the steel plants is manually made, which mainly aiming to the two key processes of converter and caster, the refining process is not scheduled and used as a buffer to ensure effective connection between processes in this kind of scheduling method. This kind of scheduling scheme which is manually formulated can only optimize the single process. In order to formulate a more rational steelmaking and continuous casting production scheduling scheme and form a linkage production operation mechanism, more and more scholars devote themselves to the research of this problem, and emerging a large number of solutions. The main algorithms include branch and bound algorithm (see Morikawa et al. (2009)), two-stage optimization algorithm (see Wang (2016)), Lagrange algorithm (see Mao et al. (2014)), and the intelligent optimization algorithms that belongs to the approximation algorithm. The accurate algorithms are often applied to solve simple problems with low complexity and small scale, and the intelligent optimization algorithms ((see Li et al. (2009) and Zhu et al. (2010))) have attracted a lot attention, because they are more suitable to solve those problems with higher complexity and bigger scale. Among them, the genetic algorithm(GA) and its improved algorithms are the most widely used because of their excellent properties.

SUN et al. apply GA to solve steelmaking and continuous casting scheduling problems with single refining (see Sun et al. (2010)). However, due to its poor local search ability, low search efficiency at the latter stage of evolution, and it's easy to premature convergence, the traditional GA is not suitable to solve multi-objective optimization problem of steelmaking and continuous casting with multiple refining.

WANG et al. use NSGA2 to study the scheduling problem of steelmaking and continuous casting production process (see Wang et al. (2015)). In the process of selecting the next generation of individuals, in order to make individual selection more reasonable, NSGA2 has improved the process. The parent population and the offspring population are merged into double population firstly, these individuals in the double population are given a non-dominant rank, and calculated the individual crowding degree. These individuals are selected to constitute a new sub-population according to elitist strategy. By extending the range of the population, the diversity of the population is enriched, preserving all the best individuals in the evolutionary process, thereby improving the accuracy of the optimization. The study of the paper (Wang et al. (2015)) fully proves the superiority of NSGA2 to solve the scheduling problem of steelmaking and continuous casting with single refinery. However, the paper has not given the strategy of how to choose the optimal solution when using NSGA2 to solve the problem. In practical applications, it is difficult for decision makers to pick out the only solution as the optimal solution to formulate the scheduling scheme, since a series of Pareto solutions are usually obtained when solving multi-objective problems with NSGA2. As a result, there will be major limitations in applying the NSGA algorithm to solve such practical problems (see Sivasubramani et al. (2011) and Jiang et al. (2014)).

In this paper, NSGA2 is used to solve the problem of complex steelmaking and continuous casting production scheduling with multiple refining. At first, the multi-objective optimization scheduling model is established according to production process and schedule requirements, and then NSGA2 is used to solve the scheduling model. Finally, the fuzzy decision making method is introduced to determine the optimal scheme for the dispatchers to avoid the selection of subjective preferences. The superiority of this method used to solve the problem of lacking the scientific basis for selection of the optimal solution is verified in other fields (see Ye et al. (2013)).

2. DESCRIPTION OF STEELMAKING AND CONTINUOUS CASTING PROCESS

The steelmaking and continuous casting production process of a steel plant is illustrated in Fig. 1, which mainly includes three processes, i.e. steelmaking, refining and continuous casting. In the steelmaking stage, carbon, manganese, sulfur, phosphorus and other elements in the molten iron are oxidized to obtain the molten steel that meets the requirements of steelmaking. Then, the molten steel is poured into the ladle and transported to the appropriate refining device for refining. In the refining stage, the molten steel is removed sulfur and impurities; its temperature is adjusted to meet the requirements of continuous casting. According to the different number of refining device that treat molten steel, the refining process is separately named as single refining, double refining, triple refining. After the refining process, the ladle with high quality molten steel is transported to the specified continuous casting machine and is ready for casting. The molten steel is injected into the tundish, cooled rapidly and solidified into casting blank under the action of crystallizer. The casting blank connected to the dummy bar are pulled out of the crystallizer, cooled and cut to a certain length to meet the sales demand.

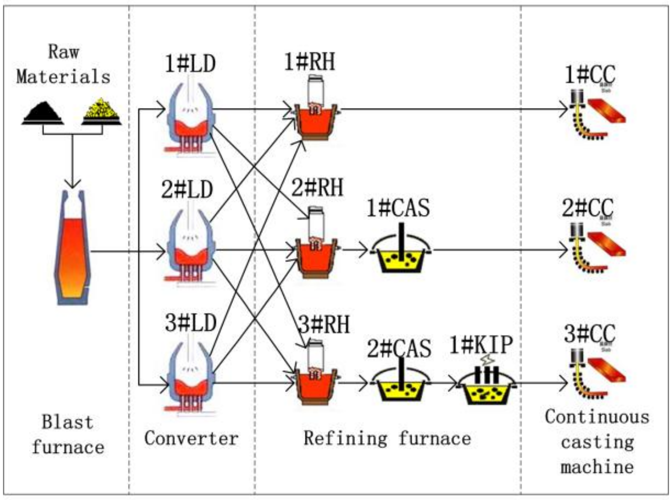

Fig. 1. Steelmaking and continuous casting process flow chart.

3. SCHEDULING METHOD BASED ON NSGA2 FOR STEELMAKING AND CONTINUOUS CASTING SCHEDULING

In order to clearly describe the scheduling method based on NSGA2 for steelmaking and continuous casting production process, this section gives the mathematical description and symbolic description of the steelmaking and continuous casting production scheduling problem, and giving the solution process of solving problem by using the NSGA2.

3.1 Symbols and Descriptions of the Multi-Objective Mathematical Model

Table 1. Symbols and description

Symbol	Description
k	The serial number of casting, $k=1,2,...,K$;
Ω_k	The charge set of the $k-th$ casting;
i	The serial number of charge, $i \in \Omega_k$;
i'	On the same device, the next charge after the charge i , $i \in \Omega_k$;
j	The serial number of the procedure which the charge undergoes, $j=1,2,\cdots,J$;
r	The serial number of the device category; $r=1$ indicates converter device, $r=2$ indicates the RH refining devices, $r=3$ indicates the CAS refining devices, $r=4$ indicates the KIP refining devices, $r=5$ indicates a kind of continuous casting machine;
$m(r)$	Indicates the $r-th$ device in the $m-th$ device category. For example, 1 (1) is the first converter of the converter device category, and 3 (5) is the third continuous casting device of the continuous casting device;
$M(r)$	The total number of $r-th$ category devices;
Π_{ki}	In the process of the $k-th$ casting, the procedure set that the $i-th$ charge is treated;
$b1_{i,j,m(r)}$	The process time of the $i-th$ charge on the $m-th$ device of the $r-th$ category device that belongs to the $j-th$ procedure;
$b2_{i,j,m(r)}^{(j+1),m'(r')}$	The time it takes for the charge i to be transported from the device m to the device m' . The device m belongs to the $r-th$ category device that treats the $j-th$ procedure. The device m' belongs to the $r'-th$ category device that treats the $(j+1)-th$ procedure;
$X_{i,j,m(r)}$	The start time of the $i-th$ charge on the $m-th$ device of the $r-th$ category device that belongs to the $j-th$ procedure;
T_k	The ideal start casting time of the $k-th$ casting;
$y_{i,j,m(r)}$	The formula is equal to 1 when the $j-th$

	step of the $i-th$ charge is treated by the $m-th$ device of the $r-th$ category device; otherwise, it is equal to 0.

3.2 Mathematical Description of the Scheduling Problem

3.2.1 Description and Constraints of Scheduling Optimization Model and Constraints

According to the optimization requirements of the scheduling, the following scheduling objectives are put forward:

The waiting time for all charges which are treated on the same device is minimal.

The total interruption time of each casting is minimal during the process of continuous casting in the same caster.

The difference between the actual start time of each casting and the specified time is minimal.

The conflict time between any adjacent charges which are treated on the same device is minimal.

Constraints are as follows:

For any two adjacent devices that treat same charges, only if the operation of the former device complete, the charge can be treated by latter device.

For the two adjacent charges treated on the same device, only if the treatment of the former is finished, the latter can be treated.

When a charge is treated in a certain process, it can only be treated by one of the device that is responsible for the process.

3.2.2 Optimal Mathematical Model of the Scheduling

$$\min\,(J1, J2, J3, J4) \tag{1}$$

$$\begin{cases} J1 = \sum_{k=1}^{K} \sum_{i\in\Omega_k} \sum_{j\in\prod ki-J} (X_{i,(j+1),m'(r')} - X_{i,j,m(r)} - b1_{i,j,m(r)} - b2_{i,j,m(r)}^{(j+1),m'(r')}) \\ J2 = \sum_{k=1}^{K} \sum_{i\in\Omega_k} (X_{(i+1),J,k} - X_{i,J,k} - b1_{i,J,k}) \\ J3 = \sum_{k=1}^{K} \left| X_{1,J,k} - T_k \right| \\ J4 = \sum_{k=1}^{K} \sum_{i',i\in\Omega_k} \sum_{j,j'\in\prod ki} (X_{i',j',m(r)} - X_{i,j,m(r)} - b1_{i,j,m(r)}) \end{cases}$$

Constraints:

$$X_{i',j',m(r)} - X_{i,j,m(r)} \geq b1_{i,j,m(r)} \qquad i\in\Omega_k, j\in\prod ki \tag{2}$$

$$X_{i,(j+1),m'(r')} - X_{i,j,m(r)} \geq b1_{i,j,m(r)} + b2_{i,j,m(r)}^{(j+1),m'(r')} \quad i\in\Omega_k, j\in\prod ki \tag{3}$$

$$\sum_{m=1}^{M(r)} y_{i,j,m(r)} = 1 \tag{4}$$

In the formula (1), $J1$ indicates that the sum of the waiting times for all charges treated on the devices is minimal; $J2$ indicates that the time interval between any two adjacent charges in the same casting is minimal; $J3$ indicates that the difference between the actual start time of each casting and the specified time is minimal; $J4$ indicates that the collision time of any two charges belonging to different casting that are treated on the same device is minimal.

The formula (2) indicates that there are any two adjacent devices of the same charge; the charge can be treated by latter device, only if after completing the operation of the former device.

The formula (3) indicates that there are any two adjacent charges treated on the same device, the latter can be treated, only if the treatment of the former is finished.

The formula (4) indicates that when a charge is treated in a certain process, it can only be treated by one of the devices that is responsible for the process.

3.3 Optimization Scheduling Algorithm based on NSGA2 for Steelmaking and Continuous Casting Production

3.3.1 Related Concepts

Coding method: Supposed that there are I charges to be treated, each charge must undergo J processes, each process has M_j ,$(j=1,2,...,J)$ machines, and there is at least one process that contains parallel machines. The chromosome code is constructed as $[m_{11}, m_{12} \cdots m_{1I}, m_{21}, \cdots m_{2I}, \cdots, m_{J1}, \cdots m_{JI}]$. Every code contains J sections, corresponding to J processes that each charge undergoes. Each segment contains I genes corresponding to I charges. The gene m_{ij} is an integer which belongs to the range $[1, M_j], (j=1,2,\cdots J)$, indicates the machine number selected to treat the process J that the charge i, $(i=1,2,...,I)$ undergoes. The coding scheme achieves that each chromosome code has a unique corresponding production scheduling scheme.

Fast non-dominated sorting: the individual q stands for any individual in the population Q. Every individual is set with two parameters of w_q and n_q, which respectively represent the set of all individual dominated by individual q and the number of individuals that dominate q .The steps are as follows: Add all individuals with $w_q = 0$ in the population Q into the set S_1, and set the corresponding non-dominated rank of the individual as F_q ; For each individual q in the current set S_1 , traversing each individual i in the set of individuals dominated by q , execute $n_i = n_i - 1$, put all individuals with $n_i = 0$ into another set N ; Assign all of the individuals in the set S_1 to the first non-dominating layer, and set the set N as the set to be treated at the moment; Repeat the above operations until the entire population is ranked.

Crowding degree: The crowding degree refers to the density of individuals around a given point in a population, it is an important to ensure the diversity of population. The steps are as follows: Initialize every individual's crowding degree to zero, i.e. $c_i = 0$; in a population containing N individuals, suppose there are M objective functions, the individuals are sorted M times based on the value of the each target function, getting M sort sequences. The crowding degree of two individuals that locate in the boundary of the population is infinite, i.e. $c_1 = c_N = \infty$. The crowding degrees of the other individuals are calculated by using the formula $c_i = \sum_{m=1}^{M} |f_m(i+1) - f_m(i-1)|$, where $f_m(i)$ indicates the function value of the m target function of the $i-th$ individual, $i-1$ and $i+1$ represent $(i-1)th$ individual and $(i+1)th$ individual in $m-th$ sequence, respectively. Repeat the above operations to determine the crowding degree of every individual.

Crowded compare operator: The operator is constructed on the basis of the individual's non-dominated rank r_i and the crowding degree c_i. i and j are any two individuals in the population, if $r_i < r_j$, the individual i wins; if $r_i = r_j$, distinguish the pros and cons by comparing their crowding degree, the individual with smaller crowding degree wins.

Elite strategy: The sub-population Q_n is obtained by selection, crossover, and mutation of population P_n, and combining the two populations into a double population containing $2N$ individuals. The individuals in the double population are sorted by non-dominated sorting strategies to obtain multiple non-dominant sets, denoted as S_i, and then calculate the crowding degree of each individual in S_i. Non-dominant sets are successively added to the new population Q_{n+1} based on the non-dominant rank from the low to the high until a certain non-dominant set is found. If all individuals of the non-dominant set are added to population Q_{n+1}, the number of individuals in population Q_{n+1} is greater than or equal to N. When the number is exactly equal to N, the operation is ended; otherwise, the crowded compare operator is used to sort the individuals in the non-dominant set, and these individuals are added to the population Q_{n+1} from the front to the back until the population contains N individuals.

3.3.2 Steps of the Algorithm

$$\phi_{ij} = \frac{f_{j\max} - f_{ij}}{f_{j\max} - f_{j\min}}, j = 1, 2, ..., M; i = 1, 2, ..., N; \tag{5}$$

$$w_j = \frac{\sum_{i=1}^{N}\sum_{k=1}^{N}(\phi_{ij} - \phi_{kj})^2}{\sum_{j=1}^{M}\sum_{i=1}^{N}\sum_{k=1}^{N}(\phi_{ij} - \phi_{kj})^2} \tag{6}$$

$$\Theta' = \sum_{j=1}^{M}\phi_{ij}\omega_j, i = 1, 2, 3, ..., N \tag{7}$$

The formula (5)~(7) is the relevant formulas of fuzzy membership and variance weighting. Among them, the formula (5) is the calculation formula of the fuzzy membership degree of the objective function, the formula (6) is the calculation formula of the weight value of the target function respectively, and the formula (7) is the calculation formula of the weighted sum of the fuzzy membership degree of the objective function.

The flow chart of the algorithm is shown in Fig. 2, the detailed steps are as follows:

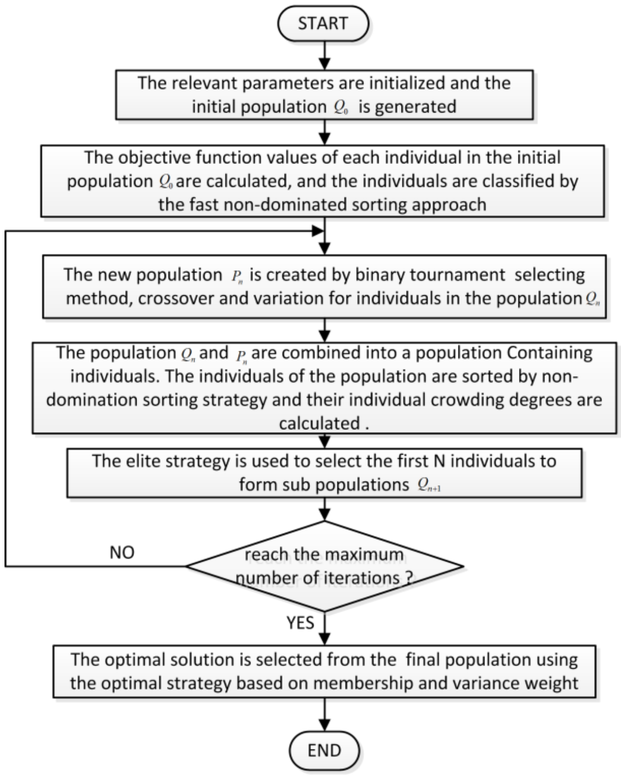

Fig. 2. Overall flow chart based on NSGA2.

Step1: Initialize the basic parameters of the algorithm and the individual code to get the initial population Q_0.

Step2: The objective function values of each individual in the initial population Q_0 are calculated, and the individuals are ranked by the fast non-dominated sorting strategy.

Step3: The new population P_n is obtained by selection, crossover, and mutation of population Q_n .

Step4: The population Q_n and P_n are combined into a double population R_n containing individuals. The individuals of the double population are ranked by non-domination sorting strategy and their individual crowding degrees are calculated.

Step5:The sub-population Q_{n+1} containing N individuals are selected from the population R_n by using the elite strategy. Determine whether the most iteration number has been reached; if yes, execute Step6; otherwise execute Step3.

Step6: By using fuzzy decision making methods based on membership degree and variance weighting, the final solution is selected from the solution set obtained by Step5. The steps of the fuzzy decision making methods are as follows：First, the membership degree of each objective function of each solution in the Pareto solution set is calculated by the formula. (5). Where N is the number of solutions, M is the number of objective functions, f_{ij} is the $i-th$ objective function value of the $j-th$ solution, $f_{j\max}$ and $f_{j\min}$ are respectively the maximum and minimum values of the $j-th$ objective function in the optimization process. Then, equation (6) is used to calculate the weight based on the variance of objective function membership, and w_j is the weight of the $j-th$ objective function. Finally, the weighted sum of the membership is obtained according to the formula (7), which is used as the choice priority of the $i-th$ Pareto solution, and is represented by Θ^i. The Pareto solution with the greatest priority value is the unbiased optimal solution of this optimization.

4. SIMULATION EXPERIMENTS

Table 2 is data of simulation experiments, which contains the initial data of three castings and 10 charges, and recording the starting time of three castings, respectively: 7:17, 7:10, 7:25.

Table 2. Initial data of three cast including ten charges

Cast Num	Charge Num	Command Num	Refining Way	Casting Equipment
1	1	115578	R	1#CC
	2	115579	R	1#CC
	3	115580	R	1#CC
	4	115769	R	1#CC
2	5	118275	C	2#CC
	6	118277	C	2#CC
	7	118281	R	2#CC
3	8	461348	R	3#CC
	9	461349	R	3#CC
	10	461350	RK	3#CC

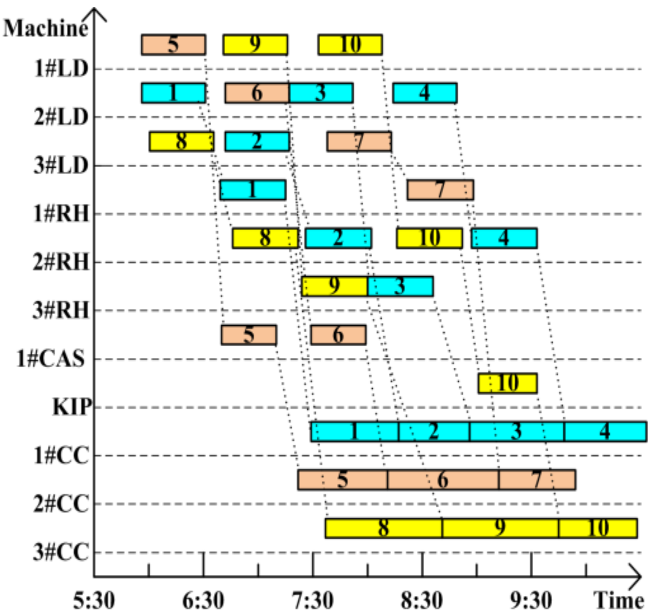

Fig. 3. Gantt chart of ten charges scheduling based on NSGA2.

Based on data of simulation experiments, four objective functions are obtained: the conflict time sum of charges that are in conflict on the same device is minimal, the total time difference between the actual start time of each casting and the specified time is minimal, the total interruption time of each castings is minimal during the process of continuous casting, the total time of all charges that wait for the processing device is the minimal. Aiming at the four objective functions, the NSGA2 is used to optimize the solution. The algorithm parameters are set to: the crossover probability is 0.4, the maximum number of iterations is 60, the population size is 100. After the algorithm iterates 60 times, it stops running and gets the Pareto solution set containing multiple solutions. Each solution in the solution set corresponds to a steelmaking and continuous casting production scheduling optimization scheme, (5)~(7) to obtain the weighted sum of membership degree of each scheduling scheme. The solution is selected as the optimal solution, whose weighted sum of fuzzy membership degree is biggest. The solution is decoded as a scheduling scheme, and the corresponding scheduling timetable (see Table 3) is formulated and the Gantt chart is drawn (see Fig. 3).

Table 3. Ten charges schedule by NSGA2

Char-ge	Converter		Refine 1		Refine 2		Casting	
	S	E	S	E	S	E	S	E
1	5:44	6:19	6:27	6:27	-	-	7:17	8:05
2	6:30	7:05	7:14	7:14	-	-	8:05	8:44
3	7:05	7:40	7:48	7:48	-	-	8:44	9:36
4	8:02	8:37	8:45	8:45	-	-	9:36	10:21
5	5:44	6:19	6:28	6:28	-	-	7:10	7:59
6	6:30	7:05	7:17	7:17	-	-	7:59	9:00
7	7:21	8:01	8:10	8:10	-	-	9:00	9:42
8	5:50	6:25	6:34	6:34	-	-	7:25	8:29
9	6:29	7:04	7:12	7:12	-	-	8:29	9:33
10	7:21	7:56	8:04	8:40	8:49	9:14	9:33	10:16

Table 4. Average running schedule

Tim-es	100 Genera-tions (s)		150 Genera-tions (s)		200 Genera-tions (s)	
	Orig-inal	Memb-ership	Orig-inal	Memb-ership	Orig-inal	Memb-ership
1	85.75	86.13	130.85	131.23	209.69	210.48
2	78.45	78.90	128.25	128.77	194.28	194.84
3	77.86	78.18	131.67	132.15	200.44	201.30
4	75.23	75.73	138.23	138.68	198.45	199.23
5	77.76	78.15	122.23	122.76	194.44	195.45
6	76.70	76.98	139.65	140.07	210.25	210.94
7	82.54	82.87	118.10	118.67	203.56	204.28
8	79.89	80.28	143.74	144.30	185.75	186.31
9	72.78	73.26	140.25	140.25	189.78	190.26
10	83.44	83.82	135.53	136.02	195.56	196.21
AVE	79.04	79.43	132.85	133.29	198.22	198.93

To verify whether the optimal solution decision method based on fuzzy membership and variance weighting will reduce the solving speed of NSGA2, aiming at the same simulation experiment data and model, the NSGA2 introducing the decision method and the original NSGA2 are used to run 10 times respectively in the case of different population size(100, 150, 200 Generations). The experimental results are shown in Table 4, and the corresponding distribution chart is drawn (see Fig. 4).

Fig. 4 shows that the two solving speed curves based on the experimental results almost coincide, which indicates that fuzzy membership and variance weighting will hardly affect the speed of NSGA2. But by using the fuzzy membership and variance weighting, the best scheduling scheme can be obtained recommend from Pareto solution set obtained by NSGA2 algorithm. The manual selection of the optimal solution needs to draw a Gantt chart(see Wang et al. (2015)) for each non dominant solution, which is time-consuming and lack of scientific basis.

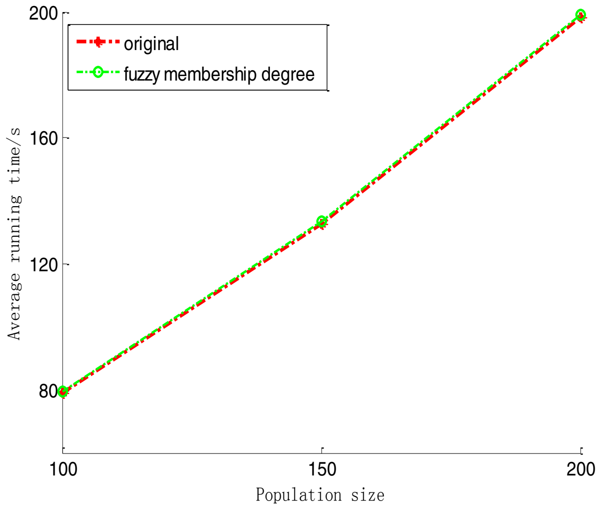

Fig. 4. Average running time distribution chart.

5. CONCLUSION

In this study, a multi-objective optimization model is established for the steelmaking and continuous casting production scheduling process with multiple refining ways, and the model is solved by NSGA2. In order to select the unbiased optimal solution from the obtained Pareto solution set, a unbiased optimal solution decision making method based on the of fuzzy membership degree and variance weighting is proposed. The simulation experiments show that the use of fuzzy membership and variance weighting can almost does not affect the solving speed of NSGA2. And by introducing membership and variance weighting decision-making methods, the optimal scheduling scheme can be provided for the decision-makers, avoiding the limitations and difficulties for decision-makers to choose the optimal solution according to the subjective preference in the actual production process. According to the simulation results, although the problem of selecting the optimal solution artificially is solved by the method of membership degree and variance weighting, the solving speed of algorithm is not very ideal, and the accuracy of the solution is not high enough. Therefore, the next step of research work is to improve the solving speed of the algorithm and the accuracy of the solution, recommending a better scheduling scheme to the decision-makers.

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