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Pareto-based Multi-criteria Evolutionary Algorithm for a Parallel Machines Scheduling Problem with Sequence-dependent Setup Times

J. Rezaeian Zeidi*, M. Zarei, K. Shokoufi

Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran

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ABSTRACT

This paper addresses an unrelated multi-machine scheduling problem with sequence-dependent setup time, release date and processing set restriction to minimize the sum of weighted earliness/tardiness penalties and the sum of completion times, which is known to be NP-hard. A Mixed Integer Programming (MIP) model is proposed to formulate the considered multi-criteria problem. Also, to solve the model for real-sized applications, a Pareto-based algorithm, namely controlled elitism non-dominated sorting genetic algorithm (CENSGA), is proposed. To validate its performance, the algorithm is examined under six performance metric measures, and compared with a Pareto-based algorithm, namely NSGA-II. The results are statistically evaluated by the Mann–Whitney test and *t*-test methods. From the obtained results based on the *t*-test, the proposed CENSGA significantly outperforms the NSGA-II in four out of six terms. Additionally, the statistical results from Mann–Whitney test show that the performance of the proposed CENSGA is better than the NSGA- II in two out of six terms. Finally, the experimental results indicate the effectiveness of the proposed algorithm for different problems.

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1. INTRODUCTION

In real manufacturing environments, managers often face several criteria and try to find the best solution that satisfies all the considerations. In most of the cases, the desired objectives are conflicting and managers require to optimize these conflicting objectives simultaneously. Hence, developing multi-objective models and algorithms are essential.

One of the well-known objective functions in multi-machine scheduling is to minimize total weighted earliness/tardiness penalties, in which jobs should be finished at times as near as possible to due dates. On the other hand, reducing the completion times causes a reduction in the number of total works-in-process (WIP) inventories. Therefore, decreasing the completion times is also one of the important objective functions [1].

Behnamian et al. [2] proposed a new hybrid meta-heuristic algorithm to solve the parallel machines scheduling problem with two objectives, namely makespan and sum of the earliness and tardiness of jobs. Zarandi and Keyvanfar [3] considered a bi-objective scheduling problem on identical parallel machines to minimize the total costs of earliness and tardiness as well as makespan. They applied a non-dominated sorting genetic algorithm II (NSGA-II) and non-dominated ranked genetic algorithm (NRGA).

Lin et al. [4] proposed two heuristics and a genetic algorithm (GA) to find non-dominated solutions to multi-objective unrelated parallel machine scheduling problems. Tavakkoli-Moghaddam et al. [5] presented a new mathematical model and a meta-heuristic method based on a GA for a multi-criteria unrelated parallel machine scheduling problem minimizing the total earliness and tardiness penalties as well as machine costs.

Tavakkoli-Moghaddam et al. [6] presented a two-level mixed-integer programming (MIP) model and a GA to solve a parallel machines scheduling problem with the objectives of the number of tardy jobs and total completion times. Amin-Tahmasbi and Tavakkoli-

* Corresponding Author's Email: *j_rezaeian@ustmb.ac.ir* (J. Rezaeian Zeidi.)

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Moghaddam [7] presented an algorithm based on a multi-objective immune system (MOIS) for a bi-objective flow shop scheduling problem with sequence-dependent setup times to minimize the total completion time and the total earliness/tardiness for all jobs.

Most of the studies have considered single-criteria algorithms. However, a new scheme of the multi-criteria algorithms has been proposed recently. These algorithms do not transform a multi-criteria problem to a single criterion one that more intensity to lead a multi-criteria procedure [8]. The NSGA-II proposed by Deb [8]is one the most well-known algorithms in this category. A controlled based version of the NSGA-II is called a controlled elitism NSGA (CENSGA) [9].

Li et al. [10] considered the problem $P_m| r_i, s_{ij} |(C_{max}, \sum T_j)$ and proposed the NSGA-II and strength Pareto evolutionary algorithm (SPEA-II). Fakhrzad et al. [11] presented a multi-objective hybrid GA for job shop scheduling with sequence-dependent setup times. The objectives are to minimize the makespan and the sum of the earliness/tardiness of jobs. They compared their algorithm with an SPEA-II. Rahmati [12] proposed the Pareto-based CENSGA for the multi-objective flexible job shop scheduling problem.

This paper addresses a multi-objective scheduling problem with sequence-dependent setup times, different release dates of jobs and processing set restrictions on m unrelated-parallel machines to minimize the total weighted earliness/tardiness penalties and the total of completion times, simultaneously.

According to the best of our knowledge, there exists no accomplished research on a multi-objective unrelated parallel machines environment considering both the total weighted earliness/tardiness penalties and the total of completion times. Following, the notation system introduced by Graham et al. [13], this problem is denoted as $R| r_j, s_{ij}, M_j | (\sum\alpha_j E_j+\beta_j T_j, \sum C_j)$ that is known to be strongly NP-hard because the sub-problem is NP-completeness [1].

The donation of our study is to propose first a MIP model. Second, we apply the CENSGA for searching Pareto-optimal solutions. Then, the proposed algorithm is compared with a benchmark based on the NSGA-II.

The rest of the paper is organized as follows. In Section 2, problem definition and notations are introduced, and then a new mathematical model is proposed. Section 3 describes the proposed multi-objective GA and solution methodology. Section 4 shows the experimental results. Finally, the conclusion and further studies are presented in Section 5.

2. PROBLEM DESCRIPTION

In this study, the problem of scheduling n different jobs on m unrelated-parallel machines is considered. Preemption is not allowed. All machines are not capable of processing all jobs. All jobs are not available for processing at time zero. The sequence-dependent setup time is considered. At any time, each machine can process at most one job, and each machine can only process one job at the same time. Also, processing times and due dates are deterministic. The test time is included in the processing time.

2. 1. Indices and Parameters

n : Number of jobs

m : Number of machines

i : Machine index ($i = 1,2, \dots, m$)

j, k : Job index ($j, k = 0,1,2, \dots, n$)

p_{ij} : Processing time of job j on machine i

d_j : Due date of job j

R_j : Release date of job j

S_{ijk} : Past-sequence-dependent setup time of job j if job k precedes job j

α_j : Earliness penalty for job j

β_j : Tardiness penalty for job j

St_j : Start time of job j

a_{ij} : 1 if job j can be processed by machine i; 0, otherwise

2.2. Decision Variables

x_{ij} : 1 if job j is processed on machine i; otherwise 0

y_{jk} : 1 if job k has been scheduled right after job j; 0, otherwise

C_j : Completion time of job j

z_j : 1 if job j is processed on machine m; 0, otherwise

E_j : Earliness of job j

T_j : Tardiness of job j

2. 3. Mathematical Model

The considered problem can be formulated by using the following MIP model:

$$\text{Min} \quad \sum_{j=1}^{n} \alpha_j E_j + \sum_{j=1}^{n} \beta_j T_j \tag{1}$$

$$\text{Min} \quad \sum_{j=1}^{n} C_j \tag{2}$$

s.t.

$$\sum_{i=1}^{m} x_{ij} = 1 \tag{3}$$

$$\sum_{j=0}^{n} y_{jk} = 1 \tag{4}$$

$$\sum_{k=0}^{m} y_{jk} \leq 1 \tag{5}$$

$$y_{jk} \leq 1 - x_{ij} + (1 - \sum_{i' \neq i} x_{i'k}) \tag{6}$$

$$x_{ij} \leq a_{ij} \tag{7}$$

$$St_k \geq \sum_{i=1}^{m} S_{jki}.x_{ik} + C_j - M.(1 - y_{jk}) \tag{8}$$

$$St_k \leq \sum_{i=1}^{m} S_{jki}.x_{ik} + C_j - M.[(1 - y_{jk}) + (1 - z_k)] \quad (9)$$

$$St_k \geq R_k \quad (10)$$

$$St_k \leq R_k + z_k.M \quad (11)$$

$$C_j = St_j + \sum_{i=1}^{m} x_{ij} * P_{ij} \quad (12)$$

$$C_j + E_j - T_j = d_j \quad (13)$$

$$x_{ik}, y_{jk} \in \{0,1\} \quad (14)$$

$$C_j, E_j, T_j \geq 0,\ j,k = 0,1,2,\dots,n, i = 1,2,\dots,m \quad (15)$$

Equations (1) and (2) represent the objective functions, which aim to minimize the weighted sum of earliness/tardiness penalties cost and the sum of completion time. Equation (3) ensures that each job is scheduled only once and processed by one machine. Equations (4) to (6) ensure that each job (but not the last scheduled job) must come immediately before, and each job (but not the first scheduled job) must come immediately after only one other job. It is assumed a dummy job 0, which always presents at the first position on each machine. Equation (7) ensures that each job is assigned to one of the machines. With regards to release dates and setup times of jobs, Equations (8) to (12) calculate the completion time of each job. Equation (13) indicates the relation between earliness and tardiness for each job.

3. NSGA-II AND CENSGA

The NSGA-II attempts to find Pareto-optimal solutions in a multi-objective optimization problem. This algorithm uses an elitist principle and emphasizes non-dominated solutions [2, 8].

The NSGA-II uses a crowding distance in their selection to maintain diversity. The mechanism is illustrated in Figure 1, where P_t indicates the main population at iteration t [12]. A mating pool is created and binary tournament selection with replacement is used to fill the mating pool, in which two solutions are selected randomly from the population and then the better solution is chosen. The one with a higher crowding distance is selected if the solutions have the same rank and the one with a lower rank is selected if the solutions are from different ranks [12].

In a mating pool, it creates a new population Q_t by using the main operators, namely crossover and mutation. To create a larger population R_t, main and new populations are merged. For inserting a dominance concept in the NSGA-II and CENSGA, fast non-dominated sorting (FNDS) is used for searching the objective of Pareto-based algorithms, which is good convergence. FNDS is performed and the solutions in R_t are sorted. The less value of FNDS means a better rank. To create the main population with the same size as P_t, it is needed to perform a selection operation [12].

The CENSGA is a developed version of the popular NSGA-II [8]. Most of the CENSGA's operators are designed, like NSGA-II. The major difference of the CENSGA with the NSGA-II is a selection strategy, in which CENSGA participates all fronts in selection through a geometric distribution [12]. See the CENSGA schematically in [8].

3. 1. Chromosome Representation

Chromosome representation determines how the problem is structured in the GA. For representing chromosomes, we use binary coding. Chromosomes are made of zero-one genes. Genes encode two pieces of information, a job and the number of the machine selected for its processing. Each gene is represented by a pair of numbers (0, 1), while 1 denotes the job being assigned to the corresponding machine and 0 means that a job is not assigned to that machine. The initial chromosomes are created and developed at random. The introduced chromosome contains all the jobs assigned to each machine and machines assigned to each job.

3. 2. Selection Method and Elitism

Another operator called a crowing distance (CD) is considered, which finds the distance between each individual in a front based on their m objectives in m-dimensional solutions space [8]. The NSGA-II and CENSGA use crowding distances in their selection to maintain diversity. A crowding distance is a measure of the objective space and is defined for solutions of the same rank.

Among two solutions with the same rank, the one with a higher crowding distance is preferable. A binary tournament selection is performed according to these two operators. The CENSGA is a developed version of the NSGA-II, in which a specific selection is done such that all fronts participate in the selection strategy [8]. This process is controlled by a geometric distribution (see Figure 2).

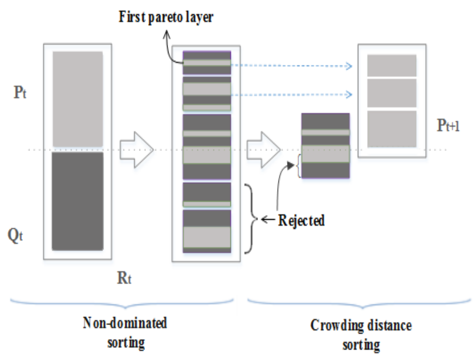

Figure 1. Evolution cycle in the NSGA-II

Equation (16) formulates this distribution. In this equation, n_i denotes the maximum number of the allowed individuals in the *i*-th front and *r* denotes the reduction rate (*r*<1). Allowed individuals in the *i*-th front and *r* denote the reduction rate (*r* <1) [8].

$$n_i = r.n_{i-1} \tag{16}$$

It is also worth to be mentioned, in a population of size *N*, the maximum number of individuals, which is allowed in each front $(i = 1,2,\ldots,k)$ is calculated by [8]:

$$n_i = N\frac{1-r}{1-r^k}r^{i-1} \tag{17}$$

3. 3. Crossover Operator The crossover operation generates offspring by combining two chromosomes' features. It has been shown in the literature that a uniform crossover works better than one- and two-point crossovers [14]. In order to do that, two chromosomes of the current generation are selected. A vector of a random number between 0 and 1 should be generated. For each gen of the chromosome, if this vector value is less than 0.7, the gen from the "first" chromosome is copied to the new chromosome; otherwise, the gen from the "second" chromosome is selected (see Figure 3) [15].

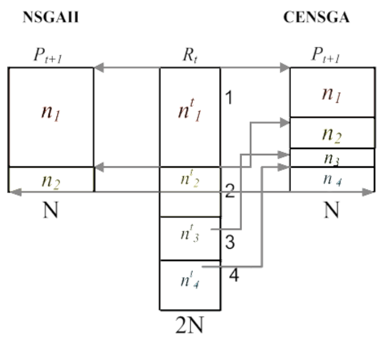

Figure 2. Selection strategy of CENSGA vs. NSGA-II

(a)	*Parent 1*	2.33	1.67	2.53	
		2.33	0.10	0.50	
		2.33	0.03		
		0.70	0.90	0.78	0.23
(b)	*Parent 2*	3.34	1.44	2.69	
		0.36	0.10	0.48	
		0.79	0.54		
		0.28	0.36	0.14	0.58
(c)	*Random numbers*	0.45	0.83	0.68	0.75
(d)	*Offspring*	2.33	1.44	2.53	
		0.23	0.10	0.50	
		0.23	0.54		
		0.70	0.36	0.78	0.58

Figure 3. Uniform crossover example

3. 4. Mutation Operator A mutation operator ensures that diversity is maintained in the population which prevents the GA from becoming trapped in 'blind corners' or 'local optima' during the search. Here, a random mutation approach is used. A gene is selected randomly and replaced with a different random number in allowed bounds.

4. EXPERIMENTAL RESULTS

This section investigates the effectiveness of the proposed algorithm and its priority to the NSGA-II. To present the efficiency of the proposed algorithm, different sets of inputs are tested. For each method, each instance is implemented 10 times and the average value of the 10 runs is considered. The algorithms are written by Matlab software on a PC with 4 GB RAM and 2.5 GHz CPU. The population and iteration size in all test problems are set to 200 and 100, respectively. P_c=85% (i.e., crossover rate), and P_m=10% (i.e., mutation rate). In the following sub-sections, the computational results of the algorithm on some multi-objective performance metrics are presented.

4. 1. Evaluation Metric A conflicting nature of Pareto archive's solutions makes us use some performance measures to have a better assessment of the proposed algorithm. So, six performance metrics are taken into account.

4. 1. 1. Mean Ideal Distance (MID) This measure presents the closeness between a Pareto solution and ideal point (0, 0), which can be shown as:

$$MID = \frac{\sum_{i=1}^{n} c_i}{n} \tag{18}$$

where n is the number of non-dominated set and $c_i = \sqrt{f_{1i}^2 + f_{2i}^2}$, and f_{1i}^2, f_{2i}^2 are the value of *i*-th non-dominated solution for the first and second objective functions, respectively [15].

4. 1. 2. Rate of Achievement to All Responses Simultaneously (*RAS*) It balances in reaching to objective functions [15].

$$RAS = \frac{\sum_{i=1}^{n}\left(\frac{f_{1i}-F_i}{F_i}\right)+\left(\frac{f_{2i}-F_i}{F_i}\right)}{n} \tag{19}$$

where $F_i = \min\{f_{1i}, f_{2i}\}$, [16]

4. 1. 3. Spread of Non-dominance Solution (*SNS*) It is a diversity measure of Pareto archive solutions [15].

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(MID-c_i)^2}{n-1}} \tag{20}$$

4. 1. 4. Spacing (S) This metric introduced by Schott [17] is used for measuring the extent of spread among the obtained solutions. It is formulated by:

$$S = \sqrt{\frac{1}{|n|}\sum_{i=1}^{n}(d_i - \bar{d})^2} \quad (21)$$

where $d_i = \underbrace{\min}_{k\in n, k\neq 1} \sum_{m=1}^{2}\left|f_m^i - f_m^k\right|$, $\bar{d} = \sum_{i=1}^{n}\frac{d_i}{|n|}$ is the mean of all d_i, and n denotes the size of the Pareto front [18].

4. 1. 5. Number of Pareto Solution (NPS) This metric is used to show the number of Pareto-optimal solutions obtained by each of the meta-heuristic algorithms [18].

4. 1. 6. RUN TIME (RT) This measure presents the computational time of meta-heuristic algorithms to obtain optimal solutions.

4. 2. Computational Results By using data given in some related articles (e.g., [1]) that are simplified models of this paper, we apply this algorithm to a number of test problems and examples. The outputs of the mentioned metrics are shown in Tables 1 and 2. Also, it should be noticed that for the *SNS* and *NPS*, big values are better, while as for the *MID*, *RAS*, *RT* and *S*, small values are better.

Now, in a total view to summarized results presented in the last row of Tables 1 and 2, the CENSGA has a better value of the *MID*, *RAS*, *SNS*, *NPS* and RT measures while as NSGA-II just has a better value of the *S* measure. These results are evaluated statistically by the means of Mann–Whitney test and *t*-test [19]. Outputs of these statistical tests are shown in Tables 3 and 4.

TABLE 1. Results of *CENSGA* on multi-objective metrics

Problem	Proposed *CENSGA*					
	MID	***RAS***	***SNS***	***S***	***NPS***	***RT(s)***
*MK*01	0.7946	0.8007	61.7481	1.9438	47	121
*MK*02	0.7211	0.731	44.919	1.9545	37	117
*MK*03	0.7192	0.7254	68.6437	1.8814	47	128
*MK*04	0.7412	0.7498	90.5682	1.8477	53	138
*MK*05	0.7363	0.74	124.69	1.7381	56	140
*MK*06	0.7319	0.7366	114.19	1.8025	35	147
*MK*07	0.7273	0.7327	128.974	1.86	37	154
*MK*08	0.7584	0.7644	151.813	1.7836	40	167
*MK*09	0.7024	0.7073	149.492	1.8225	38	172
*MK*10	0.6777	0.6825	174.333	1.795	44	184
Total value	7.3101	7.3704	1109.37	18.43	434	1468

TABLE 2. Results of NSGA-II on multi-objective metrics

Problem	Proposed NSGA-II					
	MID	***RAS***	***SNS***	***S***	***NPS***	***RT(s)***
*MK*01	0.7946	0.8007	61.7481	1.9637	12	269
*MK*02	0.7211	0.731	44.919	1.939	15	258
*MK*03	0.7192	0.7254	68.6437	1.9264	15	287
*MK*04	0.7412	0.7498	90.5682	1.8216	34	295
*MK*05	0.7363	0.74	124.69	1.7202	25	299
*MK*06	0.7319	0.7366	114.19	1.7624	26	315
*MK*07	0.7273	0.7327	128.974	1.6989	28	325
*MK*08	0.7584	0.7644	151.813	1.738	30	352
*MK*09	0.7024	0.7073	149.492	1.7296	21	361
*MK*10	0.6777	0.6825	174.333	1.6238	20	393
Total value	7.3101	7.3704	1109.37	17.9236	226	3154

TABLE 3. Statistical comparison of the proposed algorithms by using the Mann–Whitney test

Measures	Mann–Whitney test		
	***P*-value**	**Result**	**Final Result**
MID	0.075	H_0 isn't rejected	-
RAS	0.089	H_0 isn't rejected	-
SNS	0.909	H_0 isn't rejected	-
S	0.162	H_0 isn't rejected	-
RT	0.000	H_0 is rejected	*CENSGA*
NPS	0.000	H_0 is rejected	*CENSGA*

TABLE 4. Statistical comparison of the proposed algorithms by using the *t*-test

Measures	*t*-test		
	***p*-value**	**Result**	**Final Result**
MID	0.028	H_0 is rejected	CENSGA
RAS	0.027	H_0 is rejected	CENSGA
SNS	0.959	H_0 is not rejected	-
S	0.255	H_0 is not rejected	-
RT	0.000	H_0 is rejected	CENSGA
NPS	0.000	H_0 is rejected	CENSGA

The Mann–Whitney test, as a non-parametric alternative to the two-sample *t*-test is used for testing the equality of two population medians. On the other hand, the *t*-test performs a parametric hypothesis test for evaluating equality of two population means [18].

From the obtained results based on the *t*-test represented in Table 4, the CENSGA significantly outperforms the NSGA-II in terms of the *MID*, *RAS*, *RT* and *NPS* measures. But in terms of *SNS* and *S*, the two algorithms are not statistically different, which means the *t*-test does not reject the null hypothesis of equality the CENSGA and NSGA-II. In addition, the statistical results from the Mann–Whitney test indicate that the performance of the CENSGA is better than the NSGA-II in the terms of *RT* and *NPS*, and in the remained measures, the two algorithms are not statistically different. So in total, the proposed CENSGA is more efficient than the NSGA-II and recommended for the problem.

In this research, in order to exhibit real-world situation, a bi-objective scheduling problem is formulated, which simultaneously minimizes (1) the total cost of earliness/tardiness and (2) the total of completion times or flow time. In practice, the usage of both objectives is well-justified, the first objective actually focuses on the make-to-order (MTO) philosophy in supply chain management and production theory: an item should be delivered exactly when it is required by the customer, and the second one is related to WIP inventory and rapid turn-around of jobs.

5. CONCLUSION AND FUTURE STUDIES

This paper considered the multi-objective problem of scheduling unrelated parallel machines to minimize the total weighted earliness, tardiness penalties and the sum of completion times. In this paper, a Pareto-based algorithm, called CENSGA, was implemented for solving an unrelated parallel machines scheduling problem with sequence-dependent setup times and release date. Then, this algorithm was compared with the benchmark algorithm, namely NSGA-II, on some multi-objective metrics. These metrics were also analyzed statistically by the means of the comparison test. Computational results show that the obtained solutions of the proposed CENSGA are better than the NSGA-II in this field of scheduling problems.

In the future research, it may be desirable to apply other meta-heuristic algorithms to our problem and compare outcomes on this topic. In addition, presenting other performance metrics can be advantageous for this algorithm.

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Pareto-based Multi-criteria Evolutionary Algorithm for Parallel Machines Scheduling Problem with Sequence-dependent Setup Times

J. Rezaeian Zeidi, M. Zarei, K. Shokoufi

Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran

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چکیده

این تحقیق، مسئله ماشین‌های موازی نامرتبط با زمان آماده‌سازی وابسته به توالی، زمان دسترس کارها و محدودیت پردازش کارها را مورد مطالعه قرار داده است. هدف، کمینه‌سازی مجموع وزنی هزینه‌های زود کرد و دیر کرد کارها و همچنین کمینه‌سازی مجموع زمان‌های تکمیل کارها می‌باشد. برای مسئله مورد نظر، یک مدل خطی عدد صحیح مختلط ارائه گردیده شده است. همچنین از آنجایی که مسئله در دسته مسائل NP-Hard قرار دارد، برای حل مسائل در اندازه واقعی، یک الگوریتم مبتنی بر پارتو با نام CENSGA ارائه شده است. الگوریتم ارائه شده در شش معیار عملکردی با الگوریتم NSGA-II مورد مقایسه و اعتبار سنجی قرار گرفته شده است. نتایج بدست آمده به صورت آماری توسط آزمایش میانگین Mann–Whitney و آزمایش t مورد ارزیابی قرار داده شده است. نتایج حاصل از آزمایش t نشان می‌دهد که الگوریتم CENSGA در چهار معیار از شش معیار به طور قابل توجهی عملکرد بهتری نسبت به الگوریتم NSGA-II داشته است. همچنین، نتایج آماری حاصل از آزمایش میانگین Mann–Whitney نشان می‌دهد که عملکرد الگوریتم CENSGA در دو معیار از شش معیار بهتر از عملکرد الگوریتم NSGA-II بوده است. از اینرو، نتایج آزمایشات تجربی نشان دهنده کارایی بالا الگوریتم معرفی شده برای مسائل محتلف می‌باشد.

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