A Genetic Algorithm Approach to the Balanced Bus Crew Rostering Problem

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***Abstract*—This paper addresses the problem of finding an optimal assignment of duties to bus crews in a given time horizon, in such a way that the total workload should be evenly distributed. This problem is known as the balanced bus crew rostering problem. We first formulate it as an equivalent multi-level balanced assignment problem. Then, a genetic algorithm (GA) approach is proposed to solve this problem. A numerical example is used to illustrate the application of the approach. Finally, we compare the implementation results generated by the GA approach with the results generated by an algorithm proposed by Carraresi and Gallo (1984) and another heuristic algorithm proposed by Ceder (2007). The results indicate that the GA approach has a better computational performance, and can generate more balanced bus crew rosters as well as fewer rosters. This demonstrates that the GA approach is a good alternative to the balanced bus crew rostering problem. To better understand the performance of the algorithm, sensitivity analyses of relevant parameters are presented at the end of the paper.**

***Index Terms*—public transport, balanced bus crew rostering problem, multi-level balanced assignment problem, genetic algorithm, sensitivity analysis**

I. Introduction

Generally speaking, the transit-operation planning process consists of four basic components performed in sequence: (ⅰ) network route design; (ⅱ) timetable development; (ⅲ) vehicle scheduling; (ⅳ) crew scheduling [1]. Because the whole integrated planning process is extremely difficult, the four elements are usually dealt with separately when it comes into practice. Taking the outcome of former component as the input of the next component, the whole planning process then can be fulfilled in sequence. In the components described above, the bus crew rostering, a sub-problem of the bus crew scheduling, is a critical part of the planning activity, because a fair and reasonable crew rostering scheme plays a considerably important role in arousing bus crews' enthusiasm and improving their work efficiency as well as saving a large amount of costs for public-transport (PT) agencies.

The bus crew scheduling problem (BCSP) is the problem of generating and selecting a set of feasible daily duties (a.k.a., shifts, workdays or runs) to bus crews so that all vehicle blocks or trips can be covered. It includes two sub-problems: (1) duty generation; (2) duty assignment. The bus crew rostering problem (BCRP) consists in assigning bus crews to the daily duties complying with some constraints during a planning period of a given duration, e.g., a month. Generally, those constraints include: (1) the minimum number of rest hours required between two consecutive working days; (2) the maximum allowed roster hours for each roster type; (3) the maximum working hours per day, etc. The results of the crew assignment, on the one hand, should guarantee that all duties are covered, on the other hand can achieve some objectives, such as evenly distribute total workload, evenly distribute duties, minimize maximum roster duration, minimize the sum of roster costs [1], [2]. Usually different PT agencies have different goals. The balanced bus crew rostering problem (BBCRP) means that the total workload should be evenly distributed among bus crews. Because balanced bus crew rosters can significantly reduce unfairness and unfitness for bus drivers, the balanced bus crew rostering scheme is favored by bus crews.

In this paper, we focus on dealing with the BBCRP. We first formulate it as an equivalent multi-level balanced assignment problem, which is similar to the one in [3]. Then a genetic algorithm (GA)-based approach is designed to solve it. GA emulates the evolution theory of nature and is a well established heuristic method. It is a global search heuristic technique used to find accurate or approximate solutions to optimization problems [4]. More importantly, it is very simple and powerful without carefully considering restrictive assumptions about the search space. It has been widely used in transportation engineering [5]-[9]. However, parameters of GA have significant effects on its performance. How to choose the value of parameters is an important issue when using GA to solve optimization problems. To avoid blindly setting parameters of the algorithm, sensitivity analyses of these parameters are discussed in depth in the research.

The rest of this paper is organized as follows. In Section 2, the literature review about the methodology of bus crew rostering is presented. Section 3 introduces the BBCRP and then presents the mathematical model formulation. Section 4 presents the designed GA-based approach. Section 5 provides a numerical example to illustrate the application of the proposed method and also compare its implementation results with the results

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generated by other two heuristic algorithms. Parameter sensitivity analyses of the designed solution algorithm are also given in Section 5. Finally, conclusions can be found in Section 6 together with some recommendations for further studies.

II. Review of Bus Crew Rostering Methodologies

Because the BCRP involves too many factors, such as labor laws, labor agreements, transit company rules, it is one of the most time-consuming and cumbersome tasks in PT operation. Up to now, a considerable number of researchers have focused their studies on it. Early detailed reviews on staff scheduling and rostering can be found in [10], [11]. In the literature, crew rostering problems are classified into several specific areas, such as transportation systems, call centers, health care systems, and protection and emergency services. Models and solution techniques used mainly include: mathematical programming, constraint programming, heuristics, meta-heuristics, and artificial intelligence.

The BCRP is usually formulated as different mathematical models with different objectives. Carraresi and Gallo [3] first formulated it as a multi-level bottleneck assignment (MBA) problem. They proved it was NP-complete and proposed a stable solution for MBA (SSMBA) algorithm by iteratively solving a bottleneck assignment sub-problem in order to get a stable asymptotically optimal solution. Bianco *et al.* [12] adopted a similar formulation and proposed a heuristic MBA (HMBA) algorithm. Computational results showed that HMBA outperforms SSMBA in terms of the distance from optimality, but requires a longer computation time. However, they just simply assumed that the duties were qualified for all crews and failed to consider the qualification of crews. This makes the results cannot be directly put into practice. Among other relevant approaches, Catanas and Paixao [13], Caprara *et al.* [14], Sodhi and Norris [15] formulated the BCRP based on a set covering or partitioning model. Lagrangian relaxation and decomposition are usually employed to improve the lower bound of solutions. Cappanera and Gallo [16] formulated the problem as a 0-1 multi-commodity flow problem and solved it with CPLEX. Moz *et al.* [17] considered the non-cyclic rostering context and formulated the problem as a bi-objective mathematical model and two evolutionary heuristics were designed to solve it. Mesquita *et al.* [18] proposed a binary non-linear multi-objective mathematical formulation to integrate the vehicle and crew rostering problems. Their methods can consider both PT agency's interests and driver's preferences. Aringhieri *et al.* [19] discussed the problem of determining a balanced rostering for drivers with limited skills, and three alternative formulations and solution algorithms for the problem were proposed. Actually, their heuristic algorithms were based on [3].

Although some valuable mathematical models and solution algorithms have been proposed for the BCRP, to the best of our knowledge, little attention has been paid to BBCRP. Since good bus crew rostering scheme is very important for both bus crews and PT agencies, it is very necessary to formulate more practical mathematical models and develop more efficient solution algorithms.

III. Problem Description and Mathematical Formulation

After crew duties are generated, PT operators assign these duties to bus crews in a set of predefined patterns for a specified time horizon, e.g., a month. Each pattern is called as a roster, which covers a set of duties over an amount of consecutive days. The length in time of each roster is the sum of the length in time of all the duties it contains. Rosters then repeat themselves and crews shift between each roster in the future. Generally speaking, bus crews expect that the length of each roster is almost the same so that they will feel fair and there is also no unfitness when they transfer from one roster to another.

Before giving the mathematical formulation of the BBCRP, some definitions are introduced first. Given a time horizon of $|I|$ days, for each day $|J|$ duties are generated. Let black nodes denote real duties and white nodes denote dummy duties. Let d_j^i denotes the $j-$th duty of day i , and the weight of the corresponding node is t_j^i , which equals to the length in time of the $j-$th duty of day i . A feasible crew assignment to a single crew corresponds to a path from one of the nodes in the first node set to one of the nodes in the $|I|-$th node set. Its total workload (length in time) is given by the sum of the weights of all the nodes in the path. The problem can be illustrated as a weighted multi-level graph shown in Fig. 1. The BBCRP can be described as the problem of finding $|J|$ disjoint paths from the first node set to the last one such that all paths have almost the same length as well as all nodes are linked.

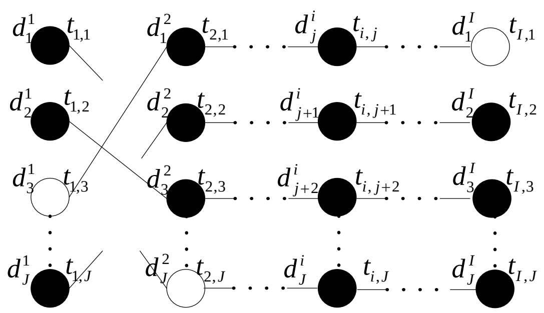

Figure 1. A weighted multi-level graph illustrating the BBCRP.

This problem is known as the MBA problem. What is more, taking into consideration of the legality of duties and the qualification of bus crews, the proposed mathematical model for the BBCRP can be given as follows:

$$\text{Minimize: } \sigma = \sqrt{\frac{1}{|J|-1}\sum_{j=1}^{|J|}\left(l_{|I|,j} - \frac{1}{|J|}\sum_{j=1}^{|J|} l_{|I|,j}\right)^2} \quad \text{ringind} \quad (1)$$

Subject to:

$$l_{1,j} = t_{1,j} \qquad \forall j \in J(1) \tag{2}$$

$$l_{i,j} = t_{i,j} + \sum t_{i-1,j} x_{i-1,j,k} \quad \forall j \in J(i), k \in K(i), i \in I, t_{i,j} \in t \tag{3}$$

$$\sum_{k \in K(i+1)} x_{i,j,k} = 1 \qquad \forall \; j \in J(i), i \in I \tag{4}$$

$$\sum_{j \in J(i)} x_{i,j,k} = 1 \qquad \forall k \in K(i+1), i \in I \tag{5}$$

$$x_{i,j,k} = 0 \text{ or } 1 \qquad \forall j \in J(i), k \in K(i), i \in I \tag{6}$$

where $x_{i,j,k}$ =1 if duty k of day $i+1$ can be assigned to a bus crew who is qualified to perform duty j of day i, 0 if not. Let *Tabu List*=$[x_{i,j,k}], \forall j \in J(i), k \in K(i), i \in I$ denotes the set of unfeasible links, which means that duty k of day $i+1$ cannot be assigned to the crews who perform duty j of day i. Let $\mathbf{t}$ denotes the time length distribution matrix. Let $l_{i,j}$ denotes the total workload from day 1 to day i of the crew performing duty j of day i. Clearly the total workload for a crew in a given time horizon is $l_{|I|,j}$. $|I|$ and $|J(i)|$ represent the number of rostering days and the number of duties of day i, respectively. The standard deviation of the length of all the $|J(i)|_{i=1}$ rosters is denoted by σ.

Our goal is to generate balanced rosters, which means minimizing σ. Carraresi and Gallo [3] presented a similar mathematical formulation, but their objective is to minimize the length of the longest roster, hoping through this way to obtain balanced rosters. They also formulated it as an MBA problem and proved that it was NP-complete, and proposed an asymptotically optimal algorithm for it. However, the algorithm cannot guarantee that all rosters have the same length and it also fail to consider the legality of duties and bus crews' qualification for duties. In the next section, we will introduce a GA-based approach to solve the above mathematical model, which can take into account the preference and qualification of bus crews.

IV. Proposed GA Approach

In this section, we introduce a GA approach to solve the proposed mathematical model. After the generation of balanced rosters, bus crews can shift between every two rosters, thus balanced bus crew rostering goal can be achieved.

The entire designed GA approach to the BBCRP is outlined in sequence as follows.

Step 1: Initialization

1) Encoding scheme

Real coded scheme is adopted, because it can show characteristics of individuals directly. Each chromosome has $|I|$ sections corresponding to the $|I|$ levels of the weighted multi-level graph, and each section has $|J|$ genes, a permutation of array [1 2 … $|J|$], which represents a possible link between two adjacent node sets of the weighted multi-level graph. The total number of genes of a chromosome is $|I| \times |J|$. A simple illustration of the encoding scheme is shown in Fig. 2.

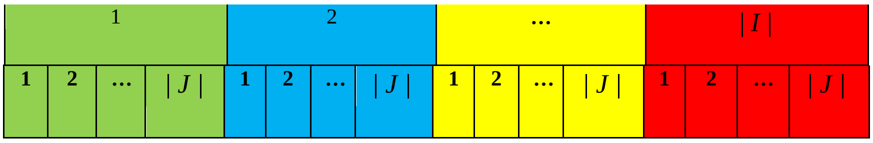

Figure 2. An illustration of the chromosome encoding scheme.

2) Define the GA parameters

This process is about the definition of some important parameters of the GA, which mainly includes the time length distribution matrix: $\mathbf{t}$, the population size: *sizepop*, the crossover probability: *pcross*, the mutation probability: *pmutation*, and the maximum iteration number: *maxgen*.

3) Generate an initial population

According to our encoding scheme, the total number of populations is $(|J|!)^{|I|}$. At beginning, a feasible solution is randomly generated as the initial population.

Step 2: Fitness Evaluation

The fitness function is defined based on the objective function σ. According to it, the fitness value F_i of each chromosome can be calculated as the following equation.

$$F_i = \frac{1}{\sigma_i} \tag{7}$$

where σ_i is the standard variation defined in equation (1).

Step 3: Selection

This step is about selecting individuals from the current population as individuals of the next generation based on their fitness value. The probability p_i of the selection of each individual is defined as follows.

$$p_i = \frac{F_i}{\sum_{i=1}^{N} F_i} \tag{8}$$

where F_i is the fitness value of individual i, and N is the number of total populations. Obviously we have $\sum_{i=1}^{N} p_i = 1$. We do the selection process using the roulette method. First, we randomly generate $p_s \in [0,1]$, if $F_i > p_s$, then individual i is chosen as an individual of the next generation. Then repeat N times and generate N individuals as the next population.

Step 4: Crossover

After two parent chromosomes are selected in step 3, two new children chromosomes are then generated by using a crossover operator. The operator means that when the operator condition is satisfied, one part of a chromosome, corresponding to one possible link between two adjacent duties, is chosen as crossover with another chromosome. A simple illustration of the crossover operator is shown in Fig. 3.

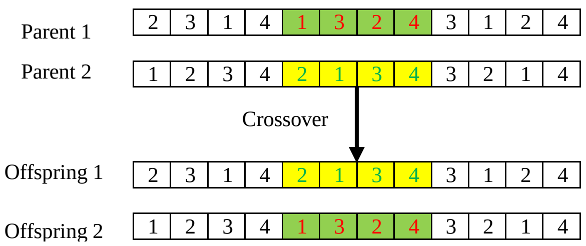

Figure 3. An illustration of the crossover operator.

The crossover operator process is finished in this way. First, a real number $p_c \in [0,1]$ is randomly generated. If the predefined crossover probability: $pcross > p_c$, then do the crossover process, and do nothing otherwise.

Step 5: Mutation

Mutation operator is adopted to avoid being trapped in local optimal and to further improve the optimization results generated in step 4. In this step, first randomly choose a chromosome. Then randomly generate a real number $p_m \in [0,1]$, if the predefined mutation probability: $pmutation > p_m$, then two genes in the same section of a chromosome randomly exchange their position. A simple illustration of the mutation operator is shown in Fig. 4.

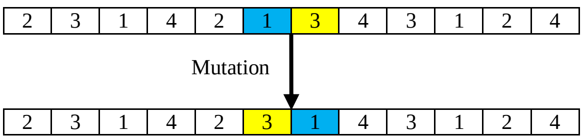

Figure 4. An illustration of the mutation operator.

Step 6: Termination

If the iteration number κ reaches the maximum iteration number: *maxgen*, then the individual with the highest fitness value is regarded as the optimal solution of the problem. Otherwise set $\kappa = \kappa + 1$ and return to step 2.

It should be noted that, in solving the BBCRP with consideration of crews' qualification of duties, the result generated by the GA approach may contain elements that belong to the *Tabu List*$=[x_{ijk}], \forall j \in J(i), k \in K(i), i \in I$, which means that the solution is unfeasible. To overcome this problem, considering the number of elements in the *Tabu List* is very small and the probability of encountering such kind of unfeasible solution is not big and also the designed GA is very simple and fast, we just implement the GA once more until generating a feasible solution and take it as a final optimal solution.

V. Computational Results

In this section, we discuss the GA implementation and parameters sensitivity analyses. First, a simple bus crew rostering problem is given. Then, we present the GA implementation results and compare them with the results generated by an algorithm proposed by Carraresi and Gallo (1984) and another heuristic algorithm proposed by Ceder (2007). At last, parameter sensitivity analyses of GA, including the population size, crossover probability, and mutation probability, are presented.

A. A Numerical Example

To illustrate the performance of the proposed GA approach and compare it with the SSMBA algorithm and Ceder's method, a simple bus crew rostering example used by Ceder (2007) is adopted in this research. The duty distribution of the example is shown in Table Ⅰ and the parameters of each duty are shown in Table Ⅱ. In this case, 10-hours is the minimum rest period required between two consecutive working days, which means that link [d_4^1---d_1^2] and link [d_4^4---d_1^5] are unfeasible links, thus $x_{141} = 0$; $x_{441} = 0$ and the *Tabu List*$=[x_{141}, x_{441}]$.

TABLE I. Input Data for the Example Problem.

	Mon.	Tue.	Wed.	Thur.	Fri.	Sat.	Sun.
Duty distribution	d_1^1	d_1^2	d_1^3	---	d_1^5	d_1^6	---
	d_2^1	d_2^2	d_2^3	d_2^4	d_2^5	---	---
	---	d_3^2	d_3^3	d_3^4	d_3^5	d_3^6	---
	d_4^1	---	d_4^3	d_4^4	---	---	d_4^7

TABLE II. Duty Parameters of the Example Problem.

Duty for day i, $i = 1,2,3,4$	Start and end time	Duty length (hours) $L_j\ (h)$
d_1^i	6:00-16:00	10
d_2^i	12:00-20:00	8
d_3^i	16:00-23:00	7
d_4^i	18:00-24:00	6

For this test example, we set the parameters of GA as follows.

Time length distribution matrix: $\mathbf{t}=\begin{bmatrix}10 & 10 & 10 & 0 & 10 & 10 & 0\\ 8 & 8 & 8 & 8 & 8 & 0 & 0\\ 0 & 7 & 7 & 7 & 7 & 7 & 0\\ 6 & 0 & 6 & 6 & 0 & 0 & 6\end{bmatrix}$;

Population size: *sizepop*=50;
Crossover probability: *pcross*=0.95;
Mutation probability: *pmutation*=0.05;
Maximum iteration number: *maxgen*=100.

The iteration results of each step of the GA are shown in Fig. 5. From it, we can see the GA performs very well and can converge to one of the optimal solutions with σ =0.5 and the lengths in time of each roster are 37h, 37h, 37h, 38h, respectively. One of the best chromosomes is [4312123431421234243134312]. The corresponding links of each roster are shown in Fig. 6.

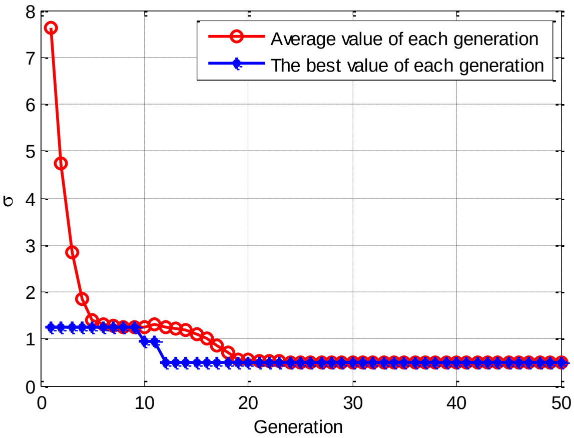

Figure 5. The minimum and average standard variations of the length of all rosters in each iteration.

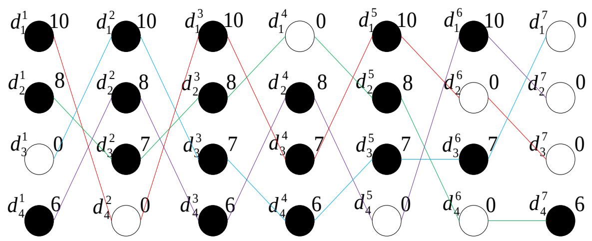

Figure 6. Network structure of the solution generated by GA.

It should be noted that the optimal solution is not unique in this example problem. For example, another chromosome [3214231441324213342124 31] is also an optimal solution. Although another chromosome [1324143232144231241313 42] seems to be also another optimal solution, however, it is unfeasible, because this solution includes element $x_{441}=1$ that is against the *Tabu List*=$[x_{141}, x_{441}]$. Therefore, to this example, it is not a feasible solution and should be abandoned. In fact, what we need to do is just finding one feasible and optimal solution for bus crews and other optimal solutions can be just discarded.

We also compare the results generated by using the GA approach and the methods used by Carraresi and Gallo (1984) and Ceder (2007). The final crew rostering results generated by using SSMBA algorithm and Ceder's method are show in Fig. 7 and Fig. 8, respectively. A detail comparison of the three approaches, including the minimum length in time of rosters $l_{\min}(h)$, the maximum length in time of rosters $l_{\max}(h)$, the standard variation of the length of all rosters σ and the number of rosters needed N, are shown in Table III.

It can be seen that the proposed GA approach have the ability of generating more balanced rosters compared to the SSMBA and Ceder's method. In addition, it generates fewer rosters than Ceder's method and the same as the SSMBA. Therefore, it can conclude that the GA approach has the best performance and is a good alternative to the balanced bus crew rostering problem.

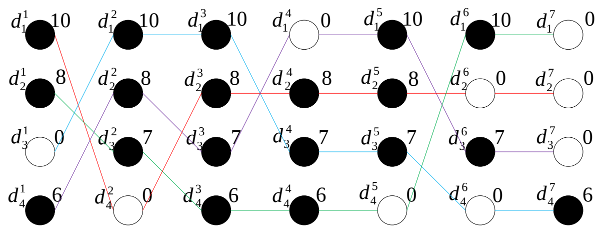

Figure 7. Network structure of the solution generated by SSMBA.

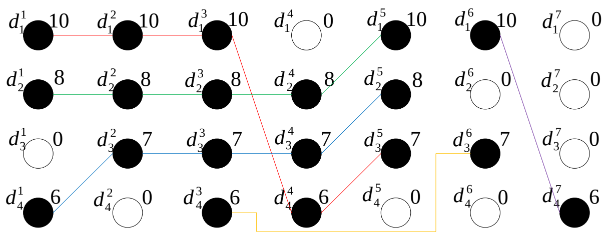

Figure 8. Network structure of the solution generated by Ceder.

TABLE III. COMPARISON OF THE RESULTS OF THE THREE APPROACHES.

Algorithm	$l_{\min}(h)$	$l_{\max}(h)$	σ	N
GA	37	38	0.50	4
SSMBA	34	40	2.50	4
Ceder	13	43	14.34	5

B. Parameters Sensitivity Analyses

To better understand the performance of the GA approach, sensitivity analyses of relevant parameters are further discussed. For the given simple example, we set the benchmark of the population size *sizepop*=50, crossover probability *pcross*=0.95 and mutation probability *pmutation*=0.05, other parameter setting see Table II and Table II. In this section, we analyze the variations of these parameters and their impacts on the performance of the GA approach.

First, the crossover probability *pcross*=0.95 and mutation probability *pmutation*=0.05 are fixed. Population size varies in the field of *sizepop* $\in$ [1 80]. Under this kind of settings, the best value of σ and the implementation time *time (s)* of each population size are shown in Fig. 9. From it, we can see the optimal value of σ in each iteration is sensitive to the population size. When the population size is 21, 40, 42, 56, 61, 73 or 75, the algorithm can converge to a solution near the optimal solution. On the other hand, with the incensement of the population size, the implementation time also increase. Therefore, to balance the convergence level and implementation time, we can set the population size as 21, 40, 42 or 56 for this example.

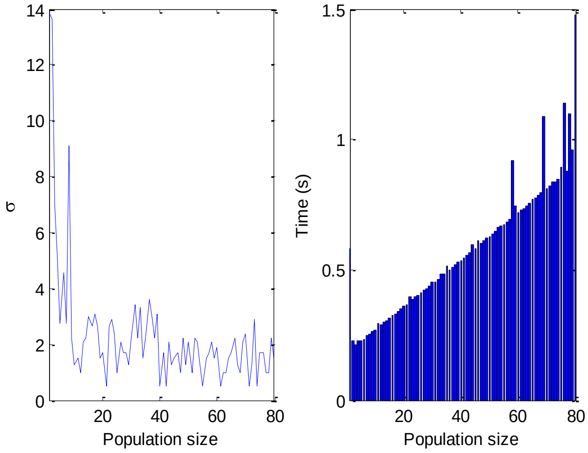

Figure 9. Results of the GA approach under different population sizes.

Second, the population size *sizepop*=50, the mutation probability *pmutation*=0.05 are fixed and the crossover probability varies in the field of *pcross* $\in$ [0.85 0.99]. The optimal value of σ and the implementation time *time (s)* are shown in Fig. 10. From it we can see the crossover probability does clearly affect the optimal solution and the result is sensitive to the crossover probability. When it is 0.97, the result converges to the optimal solution. On the other hand the implementation time, however, does not clearly increase with the incensement of the crossover probability, except when it is in 0.85 and 0.96. Therefore, the crossover probability can be set as 0.97 for this example.

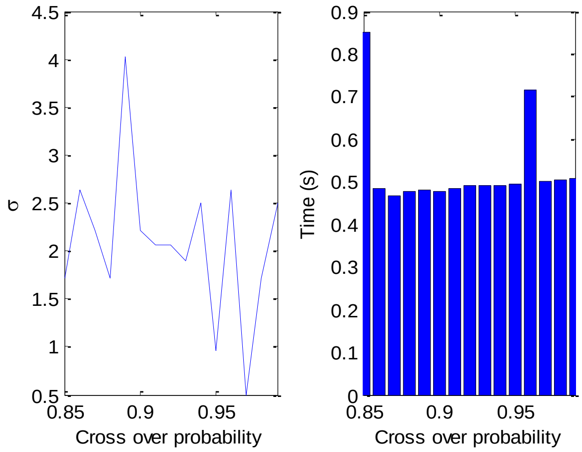

Figure 10. Results of the GA approach under different crossover probabilities.

At last, the population size *sizepop*=50, the crossover probability *pcross*=0.95 are fixed and the mutation probability varies in the field of *pmutation*= $\in$ [0.01 0.2]. The optimal value of σ and the implementation time *time (s)* are shown in Fig. 11.

From Fig. 11, we can see the result of GA is sensitive to the mutation probability. Only when it is 0.06 and 0.18, the solution can converge to the optimal solutions. The implementation time *time (s)* is kept on about 0.5 seconds except when the mutation probability is 0.01. Therefore, for this example, it can set the mutation probability *pmutation*=0.06 or 0.18.

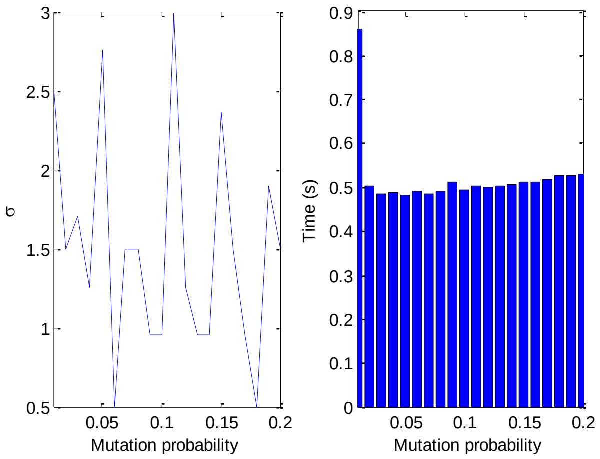

Figure 11. Results of the GA approach under different mutation probabilities.

VI. Conclusions and Discussions

This paper presents an equivalent MBA mathematical model for the BBCRP. A GA approach that can take into account the legality of duties and bus crews' individual qualifications is proposed to solve it. We compare the results generated by this approach with the results generated by the SSMBA and Ceder's approach using a numerical bus crew rostering example. It suggests that the proposed GA approach can generate the most balanced bus crew rosters as well as fewer rosters, and has the best performance among the three approaches. We also analyze the characteristics of parameters of the GA when using it to solve the BBCRP and present relevant rules to set them. The computational results show that the parameters of the GA for the test example can be set as follows: the population size can be set as 21, 40, 42, 56, 61, 73 or 75, the crossover probability can be set as 0.97, and the mutation probability can be set as 0.06 or 0.18.

As a future research topic, the following points can be considered.

- It would be worthwhile to investigate how the results could be further extended so that they can be applied to large-scale bus crew rostering problems.
- How to integrate bus crew scheduling problem and bus crew rostering problem, which means designing integrated models and solution algorithms to solve the two problems simultaneously, is also can be investigated.
- Except GA, other more efficient artificial intelligence techniques and meta-heuristics, such as simulated annealing, ant colony algorithm, tabu search, particle swarm optimization also can be analyzed to solve the BBCRP.

It can be concluded that the proposed GA approach performs well and can be further incorporated in the current computer-aided public-transport scheduling systems.

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