A Comparison of Heuristic Algorithms for Bus Dispatch

Hong Wang[1,2], Lulu Zuo[1], Jia Liu[1], Chen Yang[1(✉)], Ya Li[3(✉)], and Jaejong Baek[4(✉)]

[1] College of Management, Shenzhen University, Shenzhen 518060, China
yangc0201@gmail.com
[2] Department of Mechanical Engineering, Hong Kong Polytechnic University, Hong Kong, China
[3] School of Computer and Information Science, Southwest University, Chongqing 400715, China
liyaswu@163.com
[4] School of Computing, Informatics and Decision Systems Engineering, Arizona State University, Tempe, AZ 85281, USA
jbaek7@asu.edu

Abstract. Bus dispatch (BD) system plays an essential role to ensure the efficiency of public transportation, which has been frequently addressed by the heuristic algorithms. In this paper, five well-exploited heuristic algorithms, i.e. Genetic algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony algorithm (ABC), Bacterial Foraging Optimization (BFO) and Differential Evolution algorithm (DE), are employed and compared for solving the problem of BD. The comparison results indicate that DE is the best method in dealing with the problem of BD in terms of mean, minimum, and maximum, while BFO obtains the minor lower value of standard deviation and achieves the similar convergence speed in comparison to DE. The performance of PSO seems to outperform the remaining two algorithms (i.e. ABC and GA) in most cases. However, among five algorithms, GA achieves the worst results in terms of the weight estimated objective (i.e. number of departures and average waiting time).

Keywords: Heuristic algorithm · Multiple objective optimization · Dispatch time interval · Bus dispatch

1 Introduction

In recent years, bus dispatch (BD) system has gained the great popularity in the planning of public transportation. The operational cost of Bus Company and the satisfaction of passengers are two main objectives considered [1]. However, those two main objectives involved in BD system are contradictory. The first objective is to reduce the capital expense. However, the decrease of the operational cost of Bus Company would bring about the reduction of the number of departures, which contributes to the longer waiting time of passengers. Therefore, it is essentially important to arrange a reasonable bus dispatching interval for BD.

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Some researchers have applied the heuristic algorithms to the BD system such as GA, PSO, and BFO. A multi-objective optimization model of BD system was established in [2] to maximize bus company's interests and passengers' satisfaction, and GA was applied to solve this multiple objective problem. Wang et al. [3] presented an improvement of Particle Swarm Optimization by adopting a dispersing strategy to converge to the better solution. In [4], the BD problem that was minimizing the operation cost of bus company and the mean waiting time of all passengers was be solved by an adaptive Bacterial Foraging Optimization. Additionally, an improvement of BFO using differential evolution was proposed in [5], which adopted an adaptive strategy to update the position of the bacteria in chemotaxis process and was demonstrated to be effective in dealing with the BD problem.

Earlier studies mainly focus on the development of the improvements of the standard heuristic algorithms. To verify the performance of those earlier contributions in solving the problem of BD, this paper compares five well-exploited algorithms: BFO, PSO, ABC, GA and DE according to their efficiencies and the convergence speed. This paper is to make the comparison of the five well-exploited heuristic algorithms and discuss the advantages and disadvantages of them. Those five algorithms are all initializing the population, and evaluating the fitness of initialized individuals. The new individual is obtained through the iteration process until the optimal value is found or the termination of iterative numbers is reached.

The rest of the paper is organized as follows: Sect. 2 outlines a briefly introduction of the BD system. In Sect. 3, five heuristic algorithms are described, separately. Section 4 provides the comparison results and discussions. Finally, the summary is presented in Sect. 5.

2 Description of Problems

The BD problem [6, 7] is described as follows. The fitness function (see Eq. (1)) of BD contains two main factors: number of departures and average waiting time. To transform the two objectives as a single objective optimization problem, two weight coefficients (i.e. α and β, where $\alpha + \beta = 1$) are adopted. The mathematic formulation of BD is shown as follows:

$$fit = \alpha \times \frac{\sum_{m=1}^{M} (T_m/\Delta t_m)}{T_s/\Delta t_{\min}} + \beta \times \frac{(\sum_{m=1}^{M}\sum_{n=1}^{N} I_m \times \rho_{mn} \times \frac{\Delta t_m^2}{2}) / \sum_{m=1}^{M}\sum_{n=1}^{N} \lambda_{mn}}{\Delta t_{\max}} \tag{1}$$

s.t.

$$h_{m\min} \le \Delta t_m \le h_{m\max} \tag{2}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N} \lambda_{mn}/Q \sum_{m=1}^{M} (T_m/\Delta t_m) \ge 75\% \tag{3}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\lambda_{mn} > 2.5\times L\times\sum_{m=1}^{M}(T_m/\Delta t_m) \tag{4}$$

where $m \in (1\ldots m\ldots M)$, $n \in (1\ldots n\ldots N)$ are the m^{th} period and the n^{th} station. T_s is the total operational period. The dispatching interval in the m^{th} period is Δt_m. The time duration in the m^{th} period is T_m. The total number of departures in the m^{th} period is I_m. The arriving passenger's number and passenger's arrival rate in the m^{th} period at the n^{th} station are respectively λ_{mn} and ρ_{mn}. L represents the length of bus line and Q is the passenger capacity. While the range of Δt_m is h_{mmin} to h_{mmax} in the m^{th} period. The penalty function factor is χ, and $\chi = 1000$.

3 Heuristic Algorithms

3.1 GA

In the simulation experiment of the GA [8], the first stage is to randomly generate candidate solutions, and sort the fitness of the candidate solutions. Secondly, select the better individuals as parent solutions according to the fitness values and update new individuals through crossover and mutation. Finally, the new individuals are evaluated according to the fitness value.

3.2 PSO

In PSO [9], it is illustrated that each particle can communicate and share information with others. The particles estimate the fitness of current location and make the record of the best position p_{id} by comparing with other locations as well as the global optimal position p_{gd} by comparing with other particles. Then the new position of the particle x_{id} is updated according to the shared information and the velocity v_{id} using Eqs. (5) and (6).

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 rand(0,1)(p_{id}^{t} - x_{id}^{t}) + c_2 rand(0,1)(p_{gd}^{t} - x_{id}^{t}) \tag{5}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1},\ i = 1,\ldots,N,\ d = 1,\ldots,D \tag{6}$$

where N is particles' number, D is the dimensions of search space, and t represents the iterative number. ω indicates the inertia weight. Additionally, parameters c_1 and c_2 are acceleration factors.

3.3 ABC

The employed bee in ABC method [10, 11] represents the information of the food source. We should initialize the food source x_i firstly. Equation (7) shows the process of new food source v_i searching which will be conveyed to the onlookers. The new food source is chosen randomly by each onlooker bee according to a probability p_i provided by Eq. (8). Additionally, a scout will be employed for moving to new food sources using Eq. (9) when the performance of the employed bee cannot be improved after several evolutions.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{7}$$

$$p_i = fit_i / \sum_{n=1}^{N} fit_n \tag{8}$$

$$x_{ij} = lb_j + rand(0,1)(ub_j - lb_j),\ i = 1,\ldots N,\ j = 1,\ldots,\ D \tag{9}$$

where N is the food sources' number, while the D is the variables' number. ϕ_{ij} is a random number between 1 and –1, k is the index of a randomly selected solution, fit_i is the fitness of the i^{th} food source, lb_j and ub_j are the lower and upper limits of problem variable j.

3.4 BFO

In the standard BFO [12], chemotaxis process of bacteria containing tumbling and swimming is the major behavior for the optimal solution. The chemotaxis loop is given in Eq. (10). After that, the bacteria of weak foraging ability are waived, and the individuals with better performance are reproduced. Additionally, the elimination & disperse process is employed after the chemotactic progress to avoid getting caught in the local convergence.

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i) \times \Delta(i) / \sqrt{\Delta^T(i)\Delta(i)} \tag{10}$$

where $\theta^i(j,k,l)$ indicates the i^{th} bacterium in the j^{th} chemotactic, the k^{th} reproductive, the l^{th} elimination & dispersal step, C is the step size, and Δ is given a vector in the random direction between –1 and 1.

3.5 DE

DE [13] is a typical evolutionary method to improve the candidate solution iteratively. Equations (11) and (12) shows the process of mutation and crossing to generate new generation. If the current fitness is superior to the previous best, the best solution need to be updated.

$$v_i = x_{r1} + F(x_{r2} - x_{r3}) \tag{11}$$

$$u_{ij} = \begin{cases} v_{ij} & if(rand_j(0,1) \le CR) or\ j = j_{rand} \\ x_{ij} & otherwise \end{cases},\ i = 1,\ldots N, j = 1,\ldots,D \tag{12}$$

where N is the population size, D is the dimensionality of variables, while F is constant mutation factor. $r1$, $r2$ and $r3$ are randomly selected indexes ranging in [0, N]. CR $\in [0, 1]$ is a crossover constant and $j_{rand} \in [0, D]$ is a randomly selected index.

3.6 Pseudo-code

Table 1 shows the pseudo-code of heuristic algorithms for BD model.

Table 1. The pseudo-code of algorithms

```
Parameters initialization
Generate initial population X;
Evaluate the fitness of the population
X_best = X ;
P_best = fitness(X) ;
CheIter = 1 ;
While CheIter ≤ MaxEFs
   Update new individuals X
   Evaluate each individual fitness;
     If  fitness(X)<P_best
          X_best = X ;
          P_best = fitness(X) ;
     End
      CheIter = 1+ CheIter ;
End
Output X_best , P_best;
```

4 Simulation Test and Discussion

4.1 Parameter Settings and Encoding Fitness

Each object represents a potential solution in solving BD problem. That is $\theta = [\Delta t_1, \Delta t_2 \ldots \Delta t_D]$. If Constraint 1 (i.e. Eq. (2)) is satisfied, the solution would be a feasible for the optimization problem. Otherwise, the solution should be removed. Constraints 2 and 3 (i.e. Eqs. (3) and (4)) are the penalty functions. Thus, the fitness function of the real encoding process is formulated as follows:

$$
\begin{aligned}
fit = {} & (\alpha \times \frac{\sum_{m=1}^{M} \frac{T_m}{\Delta t_m}}{T_s / \Delta t_{\min}} + \beta \times \frac{(\sum_{m=1}^{M} \sum_{n=1}^{N} I_m \times \rho_{mn} \times \frac{\Delta t_m^2}{2}) / \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn}}{\Delta t_{\max}} + \\
& \chi \times (\left| \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn} / (Q \sum_{m=1}^{M} \frac{T_m}{\Delta t_m}) - 75\% \right| + \left| \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn} - 2.5 \times L \times \sum_{m=1}^{M} \frac{T_m}{\Delta t_m} \right|))
\end{aligned}
\tag{13}
$$

The parameters settings are referred to literature [14, 15]. The swarm size is 40, 1000 is the maximum iterations, and the operation times is set to 10 with the search space dimension 16. The crossover probability of GA is 0.65, and the mutation probability is 0.1. In BFO method, the number of swims, chemotaxis, reproduction and elimination & dispersal are separately $N_s = 4$, $N_e = 100$, $N_{re} = 5$ and $N_{ed} = 2$. $P_{ed} = 0.25$ is the probability of elimination and dispersal while the step size C is 0.1. More parameters settings of PSO and DE are displayed as follows: In PSO, $c_1 = c_2 = 1.193$, and $\omega = 0.721$; In DE, $F = CR = 0.9$.

The basic data and value of variables from the BD system are referred to [6]. The operation period is 6:00–22:00 and divides into $m = 16$ h. $n = 13$, $L = 15$ km, $Q = 60$, and $h_{m\,min} = 2$. The upper bounds of bus dispatching intervals $h_{m\,max}$ are 16, 8, 8, 16, 16, 8, 8, 16, 16, 16, 16, 8, 8, 16, 16, 16 min, separately. The volume of passenger in each time interval at each station is also in [6].

4.2 Experiment Results and Discussion

The comparison results are presented in Table 2, and the best solutions are highlighted in bold. Figures 1 and 2 shows the different average convergence curves. As shown in Table 2, the running time obtained by BFO is the longest, while GA consumes the shortest running time. In addition, DE can provide the best results of mean, minimum and maximum, and the results obtained by GA are worst. BFO and ABC almost reach to the lower standard deviation, while PSO achieves to the maximum.

The iteration processes of algorithms are drawn in terms of iterations and the corresponding optimal fitness value. From Figs. 1 and 2, DE is obviously more conductive in optimal search and converges to the better solution at earlier stage. The reason might rely on the mutation equation for DE which generates new variable at a time from previous multiple variables. Except for the DE, the BFO method is superior to other three algorithms in convergence speed. The GA and ABC methods are less conductive in comparison to other algorithms.

Table 2. The fitness values and computational cost of the algorithms

α		PSO	BFO	ABC	DE	GA
0.2	Values	0.059 ± 0.001	0.057 ± 0.001	0.061 ± 0.001	**0.053 ± 0.001**	0.062 ± 0.002
	Time	8.965	30.259	16.792	8.111	**5.604**
0.4	Values	0.115 ± 0.003	0.109 ± 0.002	0.117 ± 0.002	**0.100 ± 0.002**	0.118 ± 0.002
	Time	8.074	30.937	16.852	8.223	**5.334**
0.6	Values	0.168 ± 0.005	0.161 ± 0.002	0.171 ± 0.002	**0.143 ±** 0.003	0.172 ± 0.004
	Time	8.185	31.219	21.250	8.587	**6.224**
0.8	Values	0.224 ± 0.008	0.214 ± 0.004	0.225 ± 0.005	**0.189 ±** 0.005	0.226 ± 0.006
	Time	8.095	37.627	18.290	9.470	**6.137**

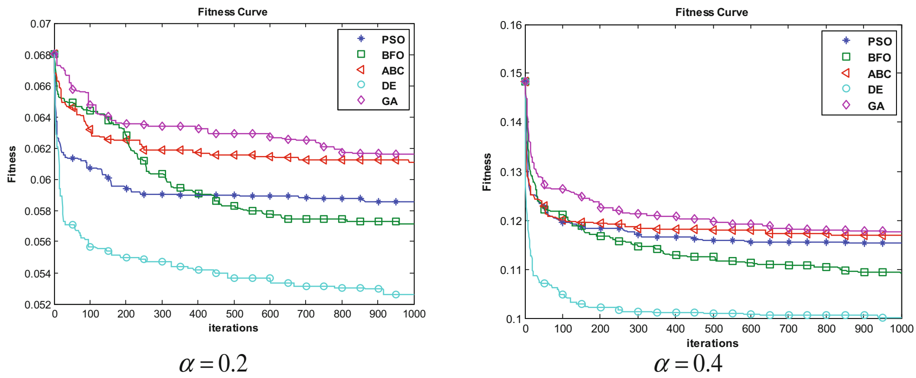

Fig. 1. The iteration process of the algorithms when $\alpha = 0.2$ and $\alpha = 0.4$

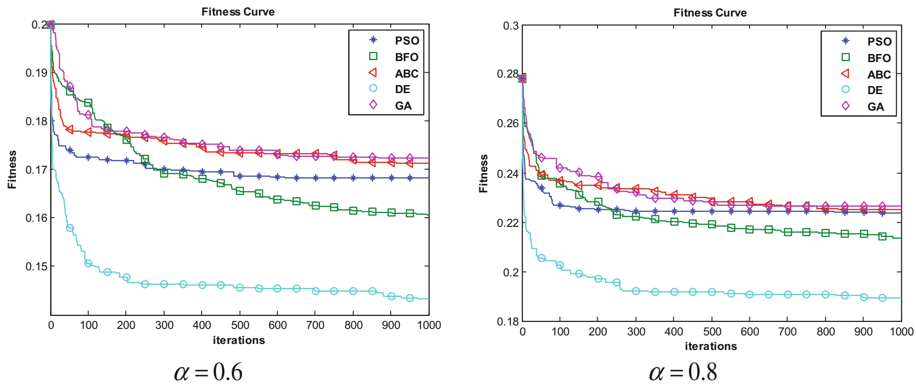

Fig. 2. The iteration process of the algorithms when $\alpha = 0.6$ and $\alpha = 0.8$

5 Conclusion

In this study, the typical heuristic algorithms have been compared in solving the problem of BD. The comparison results of the mean, minimum and maximum indicate that DE can find the best solution. In terms of the efficiency, GA can achieve the shortest running time, but the weight fitness is the worst. Though the BFO consumes larger computational complexity, the weight fitness value is also slightly worse than the DE. For the standard deviation, BFO and ABC reach to the lower standard deviation with higher stability, while PSO reaches to the maximum with larger randomness. Therefore, it is appropriate to choose the suitable algorithms according to the specific requirement in the real-applications.

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