Research Article

Jin Li, Guangyin Xu*, Zhengfeng Wang, and Zhanwu Wang

Modeling and optimization of urban rail transit scheduling with adaptive fruit fly optimization algorithm

https://doi.org/10.1515/phys-2019-0094
Received Oct 23, 2019; accepted Dec 02, 2019

Abstract: Despite the rapid development of urban rail transit in China, there are still some problems in train operation, such as low efficiency and poor punctuality. To realize a proper allocation of passenger flows and increase train frequency, this paper has proposed an improved urban rail transit scheduling model and solved the model with an adaptive fruit fly optimization algorithm (AFOA). For the benefits of both passengers and operators, the shortest average waiting time of passengers and the least train frequency are chosen as the optimization objective, and train headway is taken as the decision variable in the proposed model. To obtain higher computational efficiency and accuracy, an adaptive dynamic step size is built in the conventional FOA. Moreover, the data of urban rail transit in Zhengzhou was simulated for case study. The comparison results reveal that the proposed AFOA exhibits faster convergence speed and preferable accuracy than the conventional FOA, particle swarm optimization, and bacterial foraging optimization algorithms. Due to these superiorities, the proposed AFOA is feasible and effective for optimizing the scheduling of urban rail transit.

Keywords: Urban rail transit; Scheduling model; Train headway; Fruit fly optimization algorithm

PACS: 89.40.Bb, 07.05.Tp

***Corresponding Author: Guangyin Xu:** College of Mechanical & Electrical Engineering, Henan Agricultural University, Zhengzhou 450002, China; Email: xgy4175@126.com
Jin Li, Zhengfeng Wang, Zhanwu Wang: College of Mechanical & Electrical Engineering, Henan Agricultural University, Zhengzhou 450002, China

1 Introduction

Along with the explosive growth of economy and the rising level of urbanization in China, urban rail transit plays an increasingly important role in domestic public transport system and it develops rapidly in major and medium cities. Its advantages include less pollution, higher passenger carrying capacity, good travel speed and punctuality. As one of the core tasks of urban rail transit, departure scheduling heavily affects the operating costs, service quality and transport efficiency. Therefore, the optimization of urban rail transit scheduling has become a benchmark problem in this field.

How to accurately and efficiently allocate reasonable train intervals (train headway) becomes one of the optimization tasks for urban rail transit scheduling. Since scheduling optimization is a NP-complete problem, the traditional methods are ineffective to solve it. The nature-inspired metaheuristic algorithm is proved to be an efficient way of optimizing public transit scheduling. In [1–3], a bus scheduling optimization model is built on the basis of actual passenger flows and solved by an improved genetic algorithm. Ref. [4] takes into account the number of trains, waiting time and deadheading time to establish a mixed integer programming model and proposes an improved fruit fly optimization algorithm for the optimization of regional bus scheduling. In Ref. [5], a modified bacterial foraging optimization algorithm is used to decide the headways of bus services. However, the factors considered wherein are not comprehensive enough for all practical purposes. Ref. [6] applies the integer programming theory to study electric bus timetables. It has established a network model to optimize the solution with column generation algorithm and improved the efficiency of electric bus timetables. In ref. [7], a scheduling model is established based on the framework of intelligent bus scheduling system. It uses the hybrid of particle swarm optimization and ant colony optimization to prove the feasibility. In ref. [8], genetic algorithm is used to solve the coordination optimization model of departure times of different lines. Ref. [9] has developed an application-oriented model to estimate the waiting times so as to calculate bus departure time intervals. Ref. [10] presents a mixed-integer-programming optimization model for solving the problem of schedule synchronization and minimizing the interchange waiting times of all passengers. Ref. [11] employs genetic algorithm to solve the optimization model of train operation scheme during rush hour. Ref. [12] adopts an improved Lagrangian algorithm to solve the schedule optimization model of train. Ref. [13] uses particle swarm optimization algorithm to optimize the operation adjustment model in urban rail transit. Ref. [14] combines linear weighting method and genetic algorithm to optimize the timetable of urban rail transit.

At present, intelligent optimization algorithms have been widely used in bus transit scheduling, but few new algorithms are applied to optimize urban rail transit scheduling. Based on the real condition of urban rail transit in Zhengzhou, this paper has proposed an improved scheduling model and solved it with an adaptive fruit fly optimization algorithm (AFOA). The comparison results validate the feasibility and effectiveness of the proposed AFOA.

2 Model of urban rail transit scheduling

2.1 Model hypotheses

Urban rail transit system is much different from the bus transit system. It requires less factors to optimize the train schedule than the bus transit system. Road smoothness, traffic jam and overtaking station are not considered in the analysis of the train headway for urban rail transit system. Therefore, the results are easier and more accurate. However, to make the model more universal, some external factors need to be appropriately simplified. The following hypotheses are proposed:

1. The stopover time is fixed; the passenger flow in each period is uniformly distributed; the time when passengers get stranded at the station is not considered; and the boarding time and the time from opening to closing the doors are not taken into account;
2. Trains travel at a constant speed and no accident occurs;
3. Since urban rail transit system is a public transport infrastructure, its construction costs, revenue and expenditure are neglected, and its operating expense only include fuel and staff wages. Only ticket sales are recorded as company income. The price of subway ticket for one-way travel is fixed and passengers could go anywhere by transferring between trains.

2.2 Scheduling model

The scheduling of urban rail transit is a comprehensive work. The goal of determining the train headway is to efficiently use the transport capacity so that lower operating costs and better passenger experience could be achieved at the same time.

Passengers' satisfaction depends mainly upon commuting time and waiting time. As it is assumed that trains travel at a constant speed and travel time is not considered, waiting time becomes the key factor to ensure passengers' satisfaction. The less the waiting time, the more passenger will get satisfied. Since passengers arrive at different times, it is difficult to decompose the waiting time of individual passengers. Therefore, average waiting time is used in this paper. As the passenger flows are evenly distributed, passengers' waiting time equals to half of the headway time.

1. The satisfaction model of passengers is as follows:

$$f_p = \frac{\sum\limits_{k=1}^{K} m_k}{\frac{T_s}{(h_{\max}+h_{\min})/2}} \tag{1}$$

where f_p denotes passengers' satisfaction; k is the k^{th} period in a day; K is the set for time segments and $k = \{1, 2, \ldots K\}$; m_k is the departure times in the k^{th} period; T_s is the train service duration in a day; $h_{\max}$ and $h_{\min}$ are the maximum and minimal departure interval, respectively.
2. Model of enterprise costs
The operation costs of an enterprise mainly include fixed personnel and equipment inputs. The number of trains is the most influential factor to the costs of an enterprise. Since there is enough travel capacity to carry passengers, the costs of an enterprise will be reduced as the number of trains declines. Therefore, the model of enterprise costs is to minimize the number of trains in use.

$$f_v = \eta \frac{\sum\limits_{k=1}^{K}\sum\limits_{j=1}^{J} (m_k \rho_{kj} \Delta t_k) \Delta t_k / 2}{\sum\limits_{k=1}^{K}\sum\limits_{j=1}^{J} u_{kj}(h_{\max} + h_{\min})/2} \tag{2}$$

where f_v denotes the enterprise cost, j is the j^{th} station, J is the station set and $j = \{1, 2, \ldots J\}$, ρ_{kj} is

the passenger flow density at the j^{th} station during the k^{th} period, Δt_k is the train headway at k^{th} period, u_{kj} is the number of passenger arrivals at the station j during the k^{th} period.
Therefore, the optimization objective is to minimize the passengers' waiting time and departure times:

$$\min F = \alpha f_p + \beta f_v = \alpha \frac{\sum_{k=1}^{K} m_k}{\frac{T_s}{(h_{\max}+h_{\min})/2}} + \beta\eta \frac{\sum_{k=1}^{K}\sum_{j=1}^{J}(m_k \rho_{kj} \Delta t_k)\Delta t_k/2}{\sum_{k=1}^{K}\sum_{j=1}^{J} u_{kj}(h_{\max}+h_{\min})/2} \tag{3}$$

where α is the weighting coefficient of operation costs; β is the weighting coefficient of passenger time costs; and $\alpha + \beta = 1$ and η is the weighting coefficient of passenger comfort levels.

2.3 Constraint conditions

The running time of urban rail transit in a day can be split into 17 segments, 1 hour for each segment. The train headways corresponding to each segment are variables in the decision. The model constraints include the comfort level of passengers, revenue of the urban rail company, upper and lower limits of train headways and load factors, and the continuity of train departure.

1. Load factor

$$f_1 = \frac{\sum_{k=1}^{K}\sum_{j=1}^{J} u_{kj}}{Q_{\text{rated}} \sum_{k=1}^{K} m_k} 100\% \quad 75\% \le f_1 \le 120\% \tag{4}$$

where f_1 is the load factor in the j^{th} station during the k^{th} period, Q_{rated} denotes the rated number of passengers which a carriage is designed to carry, and f_1 is set to be above the minimum load factor to avoid the waste of public resources and below the maximum load factor for driving safety.

2. The comfort level of passengers
Another factor that directly affects citizens' interests is the level of crowdedness, *i.e.* the comfort level of passengers, which is weighted with the crowdedness coefficient η. If the number of passengers in a carriage is less than its rated capacity, it indicates that the comfort level is good, and $\eta = 1$. When the carriage become more crowded, the comfort level will decrease, and η equals to the actual passenger rate of f_1.

$$\eta = \begin{cases} 1, & f_1 \le 1 \\ f_1, & 1 < f_1 \le 1.2 \end{cases} \tag{5}$$

3. Income from ticket sales is set to be higher than operating costs.

$$f_2 = G_1 \frac{\sum_{k=1}^{K}\sum_{j=1}^{J} u_{kj}}{\sum_{k=1}^{K} m_k} - G_2 L \quad f_2 \ge 0 \tag{6}$$

where f_2 denotes the revenue of the urban rail companies, L is the total mileage of lines in operation, G_1 is average ticket price and G_2 is the average operating cost per kilometer.

4. Considering the maximum capacity of the rail route, the minimum train headway ($h_{\min}$) and the maximum train headway ($h_{\max}$) are:

$$h_{\min} \le \Delta t_k \le h_{\max} \tag{7}$$

5. To ensure the continuity of departure, the difference of train headways between two adjacent segments should not be too large, and the limit value is expressed with τ.

$$\left|(\Delta t_{k+1} - \Delta t_k) - (\Delta t_k - \Delta t_{k-1})\right| \le \tau \tag{8}$$

2.4 Objective function

Since the scheduling model contains many constraints, a penalty function is used to transform the problem of finding an optimal value with constraints into the problem of finding a sequential optimal value without constraints.

$$\begin{aligned} \min\ F(\Delta t_k, M) = \min\ F &+ M\sum_{k=1}^{K}\left[\max(0, 0.75 - f_1)\right] \\ &+ M\sum_{k=1}^{K}\left[\max(0, f_1 - 1.2)\right] \\ &+ M\sum_{k=1}^{K}\left[\max(0, -f_2)\right] \\ &+ M\sum_{k=1}^{K}\left[\max(0, h_{\min} - \Delta t_k)\right] \\ &+ M\sum_{k=1}^{K}\left[\max(0, \Delta t_k - h_{\max})\right] \\ &+ M\sum_{k=2}^{K-1}\{\max[0, |(\Delta t_{k+1} - \Delta t_k) \end{aligned} \tag{9}$$

$$-(\Delta t_k - \Delta t_{k-1})| - \tau]\}$$

where $F(\Delta t_k, M)$ is the penalty function, F is the original objective function and M is the penalty factor. The penalty factor is a large positive constant.

3 Standard FOA

The fruit fly optimization algorithm (FOA) is a bionic swarm intelligent optimization algorithm developed by Pan Wenchao [15] at Taiwan province of China. FOA is a new method for finding global optimization and it is inspired from the food finding behavior of the fruit fly. Compared with other swarm intelligent optimization algorithms, FOA is a first-order differential equation with simpler structure, easier code implementation and higher efficiency (the optimization equation of other swarm intelligent algorithms such as particle swarm optimization are second-order differential equation). Moreover, FOA only has four controller tuning parameters. While most other swarm intelligence optimization algorithms need to adjust 5-8 ones. Beyond this, the relationship and influence among these parameters are complex. If the values of control parameters are improper tuning, the performance of these algorithms will be severely affected [16]. Due to the advantages that have been mentioned above, FOA has been applied in many complex optimization fields, such as prediction [17], scheduling [18, 19], control [20, 21], logistics [22] and structural design [23]. It has become popular in the field of bio-heuristic computing.

Fruit fly is superior to other species in sensing and perception, especially in osphresis and vision. It first smells

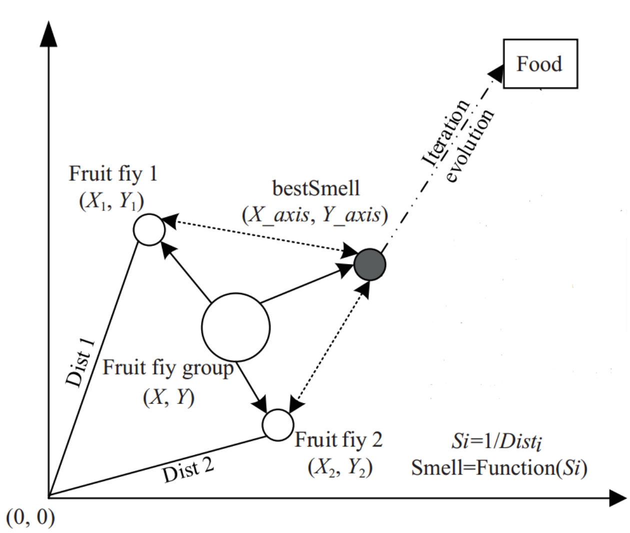

Figure 1: Search process of FOA

the lingering food odors without using vision until it approaches the food and fly to it. According to the food finding behavior, FOA can be divided into seven basic steps, as is shown in Figure 1.

1. Random initialize the location of fruit fly swarms and set the swarm size *Sizepop* and the maximum number of iterations *Maxgen*;
2. Stage of olfactory search: several fruit fly individuals are randomly generated near the center of swarm, random direction and distance of the search target are given to each individual.

$$X_i = X\_axis + RandomValue \quad (10)$$
$$Y_i = Y\_axis + RandomValue$$

3. Evaluate fruit fly individuals: at the initial stage, the distance *Dist* from the origin should be estimated first, because the fruit fly does not know where the food is, and then the judgment value of smell concentration S_i will be calculated. This value is the reciprocal of the distance:

$$Dist_i = \sqrt{X_i^2 + Y_i^2} \quad (11)$$

$$S_i = 1/Dist_i \quad (12)$$

4. Enter the smell concentration value S_i into the objective function to calculate the smell concentration *Smell* (i) of the location of fruit fly individuals:

$$Smell(i) = \mathrm{ObjFun}(S_i) \quad (13)$$

5. Visual search: the individuals with the maximal smell concentration in the fruit fly swarm are selected (finding the minimum value):

$$[bestSmell, bestindex] = \min(Smell(i)) \quad (14)$$

6. Update the center of fruit fly swarm: keep the best smell concentration value *bestSmell* and its coordinates *X* and *Y*. The fruit fly swarm then uses vision to fly to this location:

$$Smellbest = bestSmell \quad (15)$$
$$X\_axis = X(bestindex)$$
$$Y\_axis = Y(bestindex)$$

7. Enter the iterative optimization and repeat steps (2)-(5). If the current best smell concentration is better than the previous one and the number of iterations is less than *Maxgen*, perform step (6); otherwise, terminate the algorithm and export the results.

4 Adaptive FOA

Search step size is an important control parameter in FOA. When the search step size of conventional FOA is fixed, if you want to identify the results within a short time, the optimal results may not be accurate, and vice versa. When the number of fruit flies is fixed, large step size enables FOA converge fast but with low accuracy. Small step size can improve the accuracy but requires more computing time. Besides, FOA with small step size may tend to be premature and fall into local optimum. To overcome this drawback, this paper modifies the search step in standard FOA and proposes a strategy of dynamic non-linear search step, as shown in Eq. (16). According to Eq. (16), the adaptive dynamic step $C(i)$ enables FOA to take larger steps to roughly explore the promising area at the initial stage and take smaller steps to identify more accurate results at the later stage of optimization.

$$C(i) = C_{\max} a + C_{\min} \tag{16}$$

$$a = \exp\left[-30(t/T_{\max})^{s}\right] \tag{17}$$

where $C_{\max}$ is the initialized step size; $C_{\min}$ is the step size at iterative termination of algorithms; a is the adjustment coefficient of dynamic step size; t is the number of current iterations; and $T_{\max}$ is the maximum number of iterations and control parameter $s \in [1, 10]$. The relation of s, t, $T_{\max}$ and a is shown Figure 2.

The flow chart shown in Figure 3 is the proposed AFOA for solving the problem of urban rail transit scheduling, wherein the value of fitness function, *i.e.* $Smell(i)$ is taken as indicators to evaluate its performance. Therefore, $Smell(i) = \text{ObjFun}(\Delta t_k)$. Let Z be the swarm size and train headways during Δt_k as the decision variable of objective function. The total time of all segments is the problem dimensionality of fruit fly individuals. Each dimensionality corresponds to each segment. The train headway during each segment is represented by the location of a fruit fly in its corresponding dimension. Hence, the D-dimensional vector denotes the information of the fruit fly i:

$$\theta^i = \left[\theta_1^i, \theta_2^i, \cdots, \theta_D^i\right], i = 1, 2, \cdots, Z \tag{18}$$

where θ^i (d, i, j) is the location of each fruit fly, d is the dimension of each fruit fly; i is the code number of each fruit fly; and j is the number of iterations.

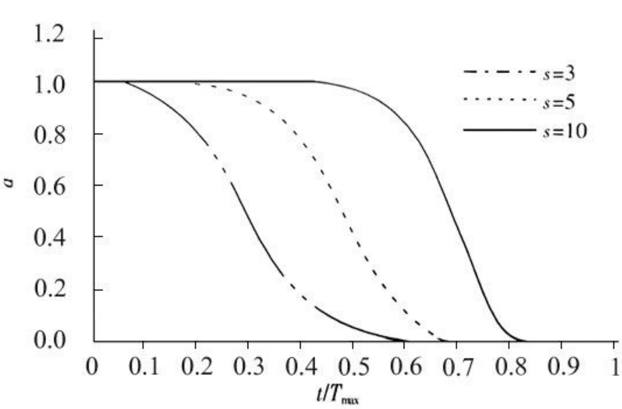

Figure 2: Distribution of adjustment coefficient *a*

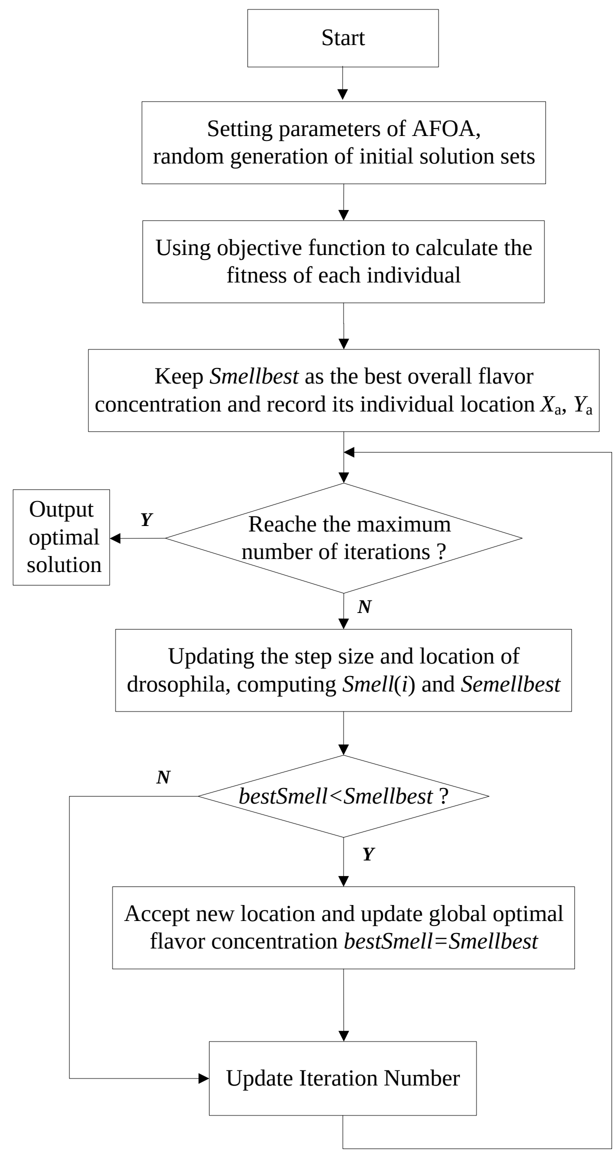

Figure 3: The flow chart of proposed AFOA

Table 1: Parameters in scheduling optimization model

Parameter	value	Parameter	value
Total line length L (km)	26.2	Weighting coefficient α	0.4
Operating time T_S (h)	17	Weighting coefficient β	0.6
Operating costs G_2 (yuan/km)	168	τ (min)	3
Number of stations J	20	Average fare G_1 (yuan)	4
Minimum departure Interval $h_{\min}$ (min)	3	Q_{rated} (number)	1460
Maximum departure interval $h_{\max}$ (min)	7	$Q_{\max}$ (number)	1870

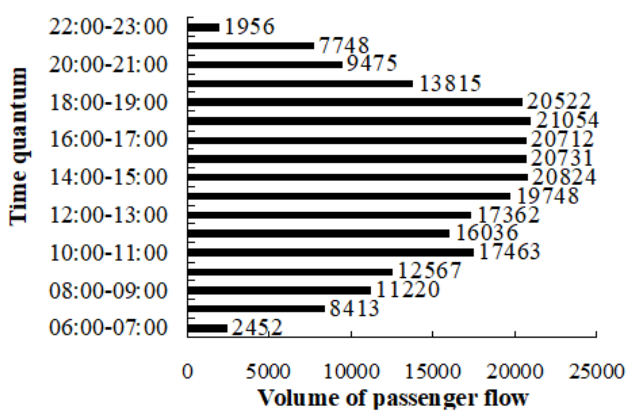

Figure 4: Distribution of passenger flow during the nonworking days for each segment

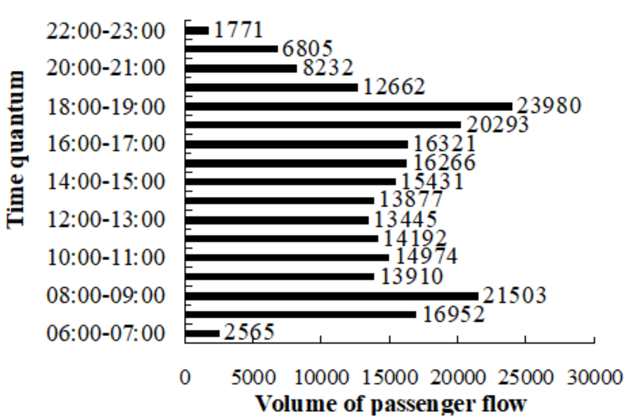

Figure 5: Distribution of passenger flow on weekdays for each segment

5 Experiment results and discussion

5.1 Instance data

For definiteness and without loss of generality, the actual operation data on general working days and nonworking days of urban rail transit Line 1 at Zhengzhou of Henan Province is selected as the research object in this paper. The inbound passenger flow data for each period are shown in Figure 4 and Figure 5, respectively. The main parameters of the scheduling model are set as Table 1.

Table 2: Full-time dynamic scheduling plan of the urban rail transit

Time quantum	Weekdays interval	Nonworking days interval
6:00-6:59	6′46″	6′57″
7:00-7:59	4′33″	5′41″
8:00-8:59	3′26″	4′48″
9:00-9:59	5′09″	4′36″
10:00-10:59	5′18″	4′24″
11:00-11:59	4′31″	5′25″
12:00-12:59	5′42″	5′18″
13:00-13:59	4′52″	5′51″
14:00-14:59	4′39″	5′48″
15:00-15:59	4′49″	5′23″
16:00-16:59	5′07″	4′57″
17:00-17:59	4′29″	5′06″
18:00-18:59	3′22″	4′51″
19:00-19:59	4′40″	5′29″
20:00-20:59	5′56″	6′11″
21:00-21:59	5′48″	6′52″
22:00-22:59	6′40″	6′58″
Total number of departures	188	198

Table 3: Current full-time scheduling with fixed headways

Peak period division	Weekdays interval	Nonworking day interval
Peak period	3′32″	4′48″
flat hump period	4′42″	
low peak period	6′06″	6′29″
Total number of departures	214	224

Table 4: Optimization results of four algorithms

Algorithm	Weekdays			Nonworking days		
	Optimal value	Average value	Number of iterations	Optimal value	Average value	Number of iterations
BFO	0.68255255	0.68421835	164	0.68254998	0.68589500	123
PSO	0.68245902	0.68316075	149	0.68248007	0.68269744	156
FOA	0.68142579	0.68195172	23	0.68157343	0.68225292	114
AFOA	0.68066397	0.68173435	7	0.68148467	0.68229395	43

5.2 Results and discussion

In this subsection, the proposed AFOA was used to optimize the scheduling model of urban rail transit. For all comparative experiments, the controller parameters of proposed AFOA were set as: the swarm size $Z = 100$; the number of iterations was 200; the dynamic step size parameters $s = 3$; $C_{\max} = 0.5$; $C_{\min} = 0.001$; and the penalty coefficient $M = 100$. To achieve a higher confidence level of comparison results, all comparative algorithms were implemented at 10 times. The optimal number of departure times and train headways for each time segment are listed in Table 2. The current fixed headways at peak time of urban rail transit are shown in Table 3. Compared with the headway schedule with fixed peak time, the optimized headway schedule in Table 2 better responded to the change in actual passenger flows during different segments of running time. It was able to improve passenger experience with more personalized service and reduce the operating costs of the company. Therefore, the proposed AFOA is proved to be feasible and efficient in optimizing the scheduling of urban rail transit.

This paper aims to verify that the proposed AFOA is more efficient than other swarm intelligence optimization algorithms in optimizing urban rail transit scheduling. Hence, it compares the optimization results of the proposed AFOA with those of standard FOA, particle swarm optimization (PSO) and bacterial foraging optimization (BFO) algorithms. To ensure a fair comparison, the numbers of swarm and iteration for all these algorithms were kept the same with swarm=100 and $T_{\max} = 200$. The controller parameters of PSO were set based on reference [4] and [24], in which learning factors $C_1 = 2$, $C_2 = 2$ and the inertia weight value decreased linearly from 0.9 to 0.4. The parameters of BFO were set based on reference [25] with chemotaxis number $N_c = 100$, replication number $N_{re} = 4$, migration number $N_{ed} = 2$ and migration probability $P_{ed} = 0.25$. The four algorithms were independently run for 10 times. Table 4 summarizes the results of the four algorithms for the optimization of scheduling model [26–28]. Figure 6 plots the convergence curves of four algorithms, indicating the proposed AFOA has better convergence speed and accuracy than BFO, PSO and standard FOA in solving the problem of urban rail transit scheduling [29–31].

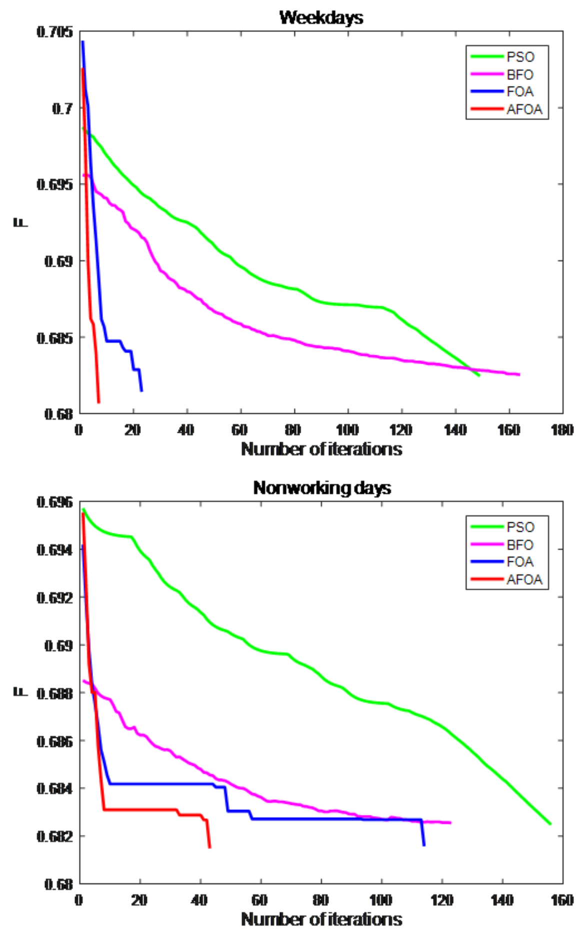

Figure 6: Convergence process of four algorithms

6 Conclusion

This paper has proposed an improved urban rail transit scheduling model and solved it with an adaptive fruit fly optimization algorithm. The comparative experimental results confirm that the proposed AFOA is accurate and efficient in obtaining the optimal train headways and timetables of urban rail transit system. Since the model parameters can be adjusted according to actual situations, the proposed model enables the staff of train companies to formulate timetables in a more convenient way. Data can be based on the latest daily and weekly passenger flows. As some external factors are simplified, some results of the model are not exactly the actual situation. Therefore, further analysis and study need to be carried out in this filed.

Acknowledgement: The authors would like to thank the anonymous reviewers for their valuable comments and insightful suggestions. This work is partly supported by the National Natural Science Foundation of China (51806061) and Henan province science and technology research project (192102110205).

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