An improved algorithm for the optimization and adjustment of urban rail transport operation order

G.M. Ma, J.W. Yan

***Abstract*—**Urban rail transport is an important traffic means; hence the adjustment of urban rail transport operation order is a quite important part. The network density is restrained due to the large construction cost of rail transport. Moreover the disturbance of random factors leads to the actual operation deviation of rail transport. To optimize the operation order of rail transport, this study optimized and adjusted the delay problem of 12 stations (from Liuyuan station to Anshan road station) along subway line 1 in Tianjin, with the improved genetic algorithm and investigated the feeder bus routes based on the balance of passenger flow volume. The research results demonstrated that the average value of population genetics and the variation of objective function became smaller with the increase of iterations and tended to be stable after 15 times of iterations; the corresponding delay gradually relieved as the train passed more and more stations and disappeared after passing the 12^{th} station; the convergence of the improved genetic algorithm used in the optimization of feeder bus network tended to be stable with the increase of iteration number. 4364.74 s was consumed to obtain the optimal solution, and the proportion of penalty cost was acceptable. Hence it is concluded that the improved genetic algorithm can help optimize the order of urban rail transport.

***Keywords*—**improved genetic algorithm, optimization and adjustment, operation, rail transport.

I. Introduction

WITH the enhancement of economic development level and the acceleration of urbanization, motor vehicles in cities has been increasingly more and urban transport pressure has become larger and larger [1]. To relieve the increasingly serious traffic pressure, some researches in China and abroad have studied urban traffic system and its structure configuration based on trip volume and demands. The emergence of urban traffic transport relieves urban traffic pressure and facilitates people's trip [2]. Currently, rail transport plays a more and more important role in the life and work of people due to the advantages of high speed, large traffic volume and high safety [3]. But rail transport needs to be optimized and improved urgently because of the existence of many interference factors. Some researchers have proposed different opinions for the optimization and improvement of urban rail transport.

Li et al. [4] divided traffic network into annular lopped network, radial network and fence network, calculated the transfer convenience indicator model and found that increasing transfer stations and loop lines was positive to the operation of rail traffic. Saidi et al. [5] proposed an optimal radial line analysis model for arbitrary demand distribution in a city, analyzed different routines based on the model, and finally put forward a cost-benefit optimization model which could be used for determining the feasibility and optimality of loop lines to optimize and adjust urban rail traffic; the evaluation suggested that the model could increase the potential net yield of loop lines. Genetic algorithm is usually used in the optimization of urban rail transport, but the traditional genetic algorithm costs too much time in calculating optimal solution due to the randomness of initial generation. To solve this problem, an improved genetic algorithm was put forward in this study. It was applied in the optimization and adjustment of delay at 12 stations (from Liuyuan station to Anshan road station) along subway line 1 in Tianjin, and moreover the balance between the delay and the passenger flow volume of feeder bus route was studied briefly.

II. Modeling

A. Automatic adjustment model

Trains operate in strict accordance with plans but may deviate because of interference [6]. Therefore an adjustment model needs to be established.

$$W(u+1) = W(u) + g(u), u = 0,1,...,n \tag{1}$$

where $W(u)$ stands for the actual operation state of trains at time point u and g stands for the state transfer operator of trains. Generally, the delay of trains is easily to be ignored. Usually, trains are moving block operation control systems without fixed block length between each other. Therefore the delay of trains can directly affect the departure time of latter trains. The calculation formula for the total delay time was:

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$$K_1 = \min\left\{\sum_{a=1}^{n}\sum_{b=1}^{m}(t_{ab}{}' - t_{ab}) + \sum_{a=1}^{n}\sum_{b=1}^{m}(v_{ab}{}' - v_{ab})\right\} \tag{2}$$

B. An optimization model for rail transport and public transit network feeder

Optimization of public transit network for balance of passenger volume in stations is the primary consideration point of the model; hence it was adjusted based on fractal-binomial-noise-driven Poisson process [7]. Specifically, passenger flow volume in rail transit stations is converted to the form of cost penalty function and moreover put into constraint and target functions; balance of passenger balance produces impacts on the calculation cost of the whole cost and even the planning of the whole feeder bus network. Therefore the constraint conditions and optimization objectives are summarized.

(1) Optimization objectives: the comprehensive cost of the whole feeder network should be minimized.

(2) Constraint conditions: only one bus in each feeder bus station provided feeder service; the starting point of the feeder route was not fixed, and the terminal point was rail transit terminal; service passenger volume in feeder route was limited; departure frequency satisfied the restriction on passenger flow volume; the passenger flow volume in bus stations satisfied capacity restriction.

Then it was calculated using formula.

$$C_\alpha(P_\beta) = \begin{cases} c_1(x - P_\beta), & X < P_\beta < x \\ 0, & x < P_\beta < y \\ c_2(P_\beta - y), & y < P_\beta < Y \\ +\infty, & P_\beta < X \ or\ P_\beta > Y \end{cases} \tag{3}$$

where $C_\alpha(P_\beta)$ refers to penalty cost, c_1 and c_2 stand for the penalty cost coefficient when passengers in rail transit stations are crowded and rare, P_β stands for the number of passengers in the β -th rail transit station, [x, y] stands for the optimal number of passengers in the β -th rail transit station, and [x, y] stands for the number of passengers that could be accepted by the β -th station. Hence the penalty cost when there were few passengers in the β -th rail transit station was:

$$C_\alpha(P_\beta) = c_1 \max[(x - P_\beta),0] \tag{4}$$

The penalty cost when passengers in rail transit stations were crowded:

$$C_\alpha(P_\beta) = c_2 \max[(P_\beta - y),0] \tag{5}$$

Hence the penalty cost when the passenger flow volume was unbalanced was:

$$C_\alpha(P_\beta) = c_1 \max[(x - P_\beta),0] + c_2 \max[(P_\beta - y),0] \tag{6}$$

Then the following model was established:

$$\begin{aligned} MinC_T &= \mu_\delta \sum_{k=1}^{K}(t_{\delta F}\sum_{\alpha=1}^{A} q_\alpha \times x_{\alpha\beta k} + \sum_{\beta=\alpha+1}^{A+B} t_{\delta T\beta}\sum_{\alpha=1}^{A} q_\alpha \times x_{\alpha\beta k} \times \sigma_{\alpha\beta}) + \mu_w\left\{\sum_{k=1}^{K}\left[\frac{1}{2F_k} + \frac{1}{2F_T}\right] \times P_k\right\} \\ &+ \mu_h \sum_{k=1}^{K}\{\frac{1}{v}\sum_{\alpha=1}^{A}[q_\alpha \times x_{\alpha\beta k} \times (\sum_{\beta=\alpha+1}^{\beta} l_{\alpha\beta k} \times x_{\alpha\beta k})]\} + \sum_{k=1}^{K}[0.5(n_k+1) \times P_k \times t_{dF}] \\ &+ \mu_h \sum_{\beta=A+1}^{A+B}\left\{(\sum_{\alpha=1}^{A} p_\alpha \times \sigma_{\alpha\beta}) \times [t_{dT} \times (B - \beta + 1) + t_{T\beta}]\right\} \\ &+ \lambda_f(2\sum_{k=1}^{K}\frac{F_k}{V} \times l_k) + \lambda_A\left(2\sum_{k=1}^{K}F_k \times l_k\right) + \lambda_h(\sum_{k=1}^{K}P_K \times t_{dF}) + \lambda_{IT}\sum_{\alpha=1}^{A}\sum_{\beta=1}^{A}\sum_{k=1}^{K}[p_\alpha \times t_{dT} \times x_{\alpha\beta k} + (F_T \times t_T)] \\ &+ \lambda_m(2\sum_{k=1}^{K}F_k \times l_k) + \lambda_\varepsilon\{(\sum_{k=1}^{K}[(\frac{F_k}{V} \times l_k) + (P_k + t_{dF}) + (F_k \times S_{k\beta})]\} \\ &\lambda_s(2\sum_{k=1}^{K}F_k \times l_k) + \sum_{B=A+1}^{A+B}\{c_1 \max[(a - P_j),0] + c_2 \max[(P_j - b),0]\} \end{aligned}$$

$x_{\alpha\beta k} = \begin{cases} 1, \\ 0, \end{cases}$, 1 means the k-th bus driving from point α to point β and 0 means else;

$\sigma_{\alpha\beta} = \begin{cases} 1, \\ 0, \end{cases}$, 1 means from bus feeder point α to railway station β and 0 means else.

In the model, C_T refers to the total operation cost of a certain line, μ_δ refers to the coefficient of passenger visit cost, μ_w refers to the cost of passengers waiting in a rail transit station, F_k refers to the operation frequency of the k-th feeder bus line, t_{dF} refers to the time of passengers getting on or off a bus in a bus station, t_{dT} refers to the time of getting on or off in a rail transit station, F_T refers to the operation frequency of rail transit, l_k refers to the operation distance of the k-th line, $t_{\delta F}$ refers to the average time of passengers visiting a bus station, q_α refers to the number of passengers at the node, and μ_h refers to the time cost coefficient of passengers travelling by rail transit.

III. Application of the Improved Genetic Algorithm

The improved genetic algorithm is generally divided into chromosome coding, initial population generation, fitness value evaluation and population evolution strategy [8]. Chromosome coding means using the minimum coded character and representing problems in a reasonable way when data are transformed to genotype data in the genetic space, including binary coding and integer coding [9]. In initial population generation, initial population is composed of several randomly generated chromosomes. In fitness value evaluation, every fitness function is corresponding to the quality of every chromosome. The calculation of fitness value of chromosomes includes chromosome decoding, objective function value calculation and fitness conversion [10, 11]. Population evolution strategy includes selection, crossover and mutation.

When the optimal solution is calculated using the traditional genetic algorithm the initial chromosome used for operation is randomly generated, which leads to low convergence speed. But urban rail transit operation plan needs to be adjusted in real time according to the actual situation, which put forward high requirements on the computing speed and result accuracy. If the initial chromosome has closed to the optimal solution, then the calculation will be accelerated. Therefore a pattern classification method [15] was designed. Historical solution value was taken as the initial chromosome when genetic algorithm was used to accelerate the convergence speed of the algorithm and improve calculation speed. To avoid removing the current solution with the highest fitness when the optimal solution was not found, the maximum number of iterations was determined using a large amount of experiments and based on the previous data. In this way, operation would stop when the number of iterations reached the preset standard; and the solution with the highest fitness could be selected as the optimal solution. The following setting was made for the urban railway experiment.

A. Chromosome coding

For the delay, arrival and departure time and interval operation time in the operation order of urban rail transit, the adjustment time was coded using integer coding. Taking the first bus at that day as an example, the departure time in the first station was 0 and the variation of time was processed by integer coding based on seconds. Suppose the departure time of the first train at the origin station as 7:00, then 7:00:30 was coded as 30.

B. Initial population generation

Initial population generates by controlling breeding range, i.e, controlling breeding boundary based on the lagging of the formulated adjustment plan compared to the original plan. By doing that, the time of initializing the location of chromosome became shorter than the previously planned time and total delay time.

C. Fitness value evaluation

The larger the fitness value of a chromosome, the stronger the chromosome adapt to environment, i.e., the better the performance. The fitness value was set as: $Fit(L)=\frac{1}{1+L}$

All the constraint conditions were hard constraints. If an individual did not satisfy all the constraint conditions, then it was eliminated to ensure the accuracy of final solution.

D. Population evolution

When reproduction probability was selected according to the current population fitness values of individuals, the number of individuals in the population was assumed as D, then the probability that an individual was selected was $P_D=\frac{Fit_a}{\sum_1^D Fit_l}$. When chromosomal chiasma was performed in an individual according to the probability of P, i.e., the position of a chromosome was changed randomly, the deficiency of important information which was randomly generated by the initial population should be prevented. When genetic algorithm stopped calculation after T, the optimal chromosome was output and the value was usually 50 ~ 800.

IV. Optimization of Rail Transit Order with Genetic Algorithm

The optimization of rail transit order with genetic algorithm was performed in MATLAB environment. Taking Tianjin Line 1 as an example, there were 22 stations. The station spacing, operation time and stopping time are shown in Table I.

Table I: Basic conditions of Tianjin Line 1

Order of station	Name	Station spacing (km)	Operation time (s)	Stopping time (s)
1	Liuyuan station	0	0	50
2	Xihengxi station	1	60	45
3	Guojiuchang station	1.1	80	45
4	Benxilu station	1.2	100	40
5	Qinjiandao station	1.5	90	45
6	Honghuli station	1.2	90	40
7	West station	1.7	90	40
8	Xibeijiao station	1.2	120	40
9	Xinanjiao station	1	90	45
10	Erweilu station	0.79	70	40
11	Haiguangsi station	1.1	90	40
12	Anshandao station	0.9	82	40
13	Yingkoudao station	0.86	75	40
14	Xiaobailou station	1.6	90	40
15	Xiawafang station	1.3	120	40
16	Nanlou station	1	80	40
17	Tucheng station	1.1	90	40
18	Chentangzhuang station	1.6	90	38
19	Fuxingmeng station	1.3	70	30
20	Huashanli station	1.3	120	35
21	University of Finance and Economics station	1.5	90	40
22	Shuanglin station	1.5	100	40

Twelve stations (from Liuyuan station to Anshandao station) were selected as the zone needing adjustment. The minimum operation time and stopping time were obtained according to Table I.

$$\min(T_\tau)=[60,60,80,100,90,90,90,120,90,70,90,82],$$

$$\min(T_b)=[50,45,45,40,45,40,40,40,45,40,40,40]$$

The parameters associated to the adjustment of train order were set as follows. Population scale was 100, hereditary algebra was 50, and crossover probability was 0.001. As to the initial state, the third train was late for 120s in the third station, and the total delay time was 420 s. In the optimization of bus feeder network, population scale was 100, length of chromosome was 20, crossover probability was 0.7, mutation probability was 0.01, and evolution terminal algebra was 50. As to the problem of bus feeder, Xinanjiao station is the transfer station for Line 1 and 2, and moreover buses passing the station included 333, 628, 837 and 860. The number of passengers at the nodes was 40, 50, 60 and 30. The distance between the two rail transit lines and the terminal point was 2 and 4 respectively.

The distance between the network nodes is shown in Table II.

Table II: The distance between the network nodes

Nodes						
	0	1.5231	1.79	2.4	2.6	2.0615
	1.5231	0	3.2597	1.457	3.2203	3.2201
	1.79	3.2697	0	3.4408	2.0225	2.3853
	2.2362	1.457	3.4408	0	2.4	4.273
Line 1	2.49	3.2201	2.0223	2.48	0	4.123
Line 2	2.0615	3.2201	2.3855	4.271	4.1232	0

The parameters involved in the bus feeder optimization are shown in Table III.

Table 3: Values of parameters

Parameter	Value (unit)
μ_δ	7 (yuan/people·h)
μ_w	4 (yuan/people·h)
t_{dF}	0.0015 (h/people)
t_{dT}	0.0006 (h/people)
F_T	22 (vehicle/h)
$t_{\delta F}$	0.125 (h)
μ_h	4 (yuan/people·h)

V. SIMULATION VERIFICATION

A. Analysis of train delay

Figs. 1 and 2 demonstrate that the variation of target function tended to be stable as the variation of population genetic values became stable gradually. After the adjustment with genetic algorithm, the delay time of all the stations gradually decreased and finally disappeared as the progress of departure timeline and station. Hence it could be concluded that optimizing train order with genetic algorithm was feasible and practical.

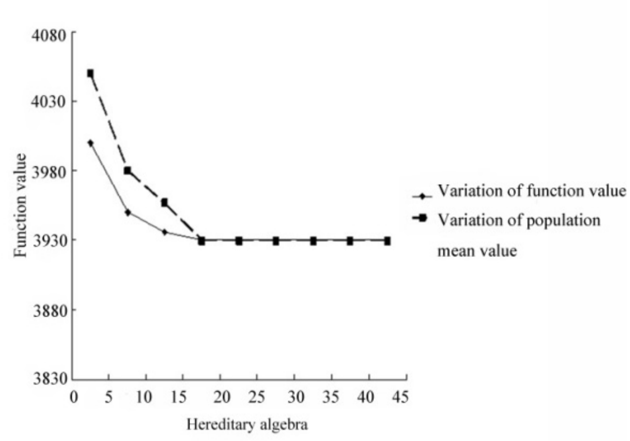

Fig. 1 Population evolution

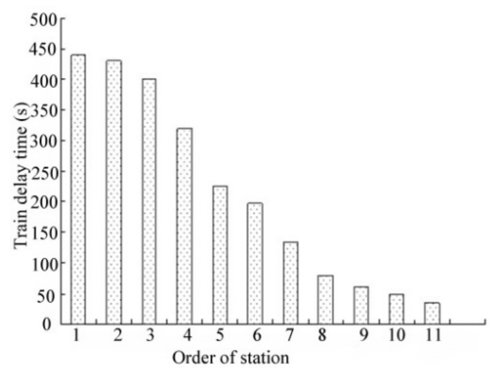

Fig. 2 Overall delay condition

B. Optimization of bus feeder lines

In Fig. 3, the result became stable and convergent when the hereditary algebra was 50, the algorithm operated for 4364.74 s, and the minimum system cost was 83857. The penalty cost is shown in Fig. 4. With the constant increase of the values of penalty coefficients, the influence of penalty in the whole cost system became larger and larger. But considering the mean dispersion tendency of passenger flow, the increase of penalty was within the normal range.

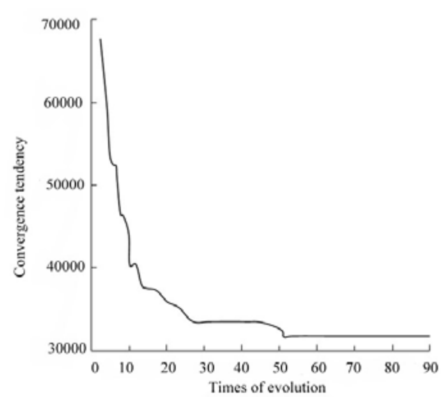

Fig. 3 Convergence curves of nodes

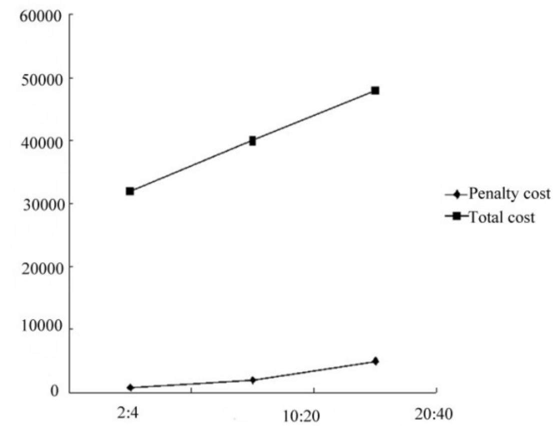

Fig. 4 Variation curves of total cost and penalty cost

VI. Discussion and Conclusion

Order maintenance and bus line feeder are the important research content in the development progress of rail transit. More and more researchers have tried to design urban transport system and its structure configuration in the perspectives of travelling characteristics and demand of citizens. Based on the last train connection, Li [12] analyzed the impacts of delay on transfer and established a static evaluation indicator system for bus line impacts. Liu et al. [13] established two route choice models for peak and off-peak hours which involved new variables including angular cost value, comfort index and personal characteristics.

The adjustment of rail transit and feeder bus routes are usually adjusted using genetic algorithm which is featured by strong searching ability, stable solution and favorable parallelism. But the calculation of the optimal solution is slow due to the high randomness. To solve this problem, the improved genetic algorithm was put forward in this study. Its difference with the traditional genetic algorithm is the initial solution. It is difficult to determine whether the randomly generated initial solution generated by the traditional genetic algorithm is close to the optimal solution. But the initial solution of the improved algorithm is obtained by pattern classification based on historical data. It is more close to the optimal solution in terms of probability.

Taking the delay problem of Tianjin subway line 1 as an example, a train automatic adjustment model was established and optimized. The cost of feeder bus was optimized in two different ways. Then the optimization schemes were simulated and tested. The average value of population genetics and the variation of objective function tended to be gentle after 15 times of iteration, and the calculation efficiency was the highest at that moment. The subway order was adjusted according to the optimized schemes. It was found that delay was relieved and even disappeared as train passed more and more stations, indicating that the improved genetic algorithm could produce positive effects to the adjustment of subway order. In the aspect of cost optimization of feeder bus route, the algorithm began to iterate from the 50-th century, and the population became stable gradually. 4364.74 s was consumed to obtain the optimal solution, and the least system cost was 83857. Moreover it was found that the penalty cost tended to occupy a larger proportion in the system cost with the increase of penalty coefficient. But considering that the distribution of passenger flow became more and more even, the increase of the penalty cost was within the normal range. In conclusion, the improved genetic algorithm could effectively optimize the cost of feeder bus routes.

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