International Journal of Innovative Computing, Information and Control
Volume **16**, Number **1**, February **2020**

ICIC International ©2020 ISSN 1349-4198
pp. **241–256**

AN IMPROVED MEMETIC ALGORITHM FOR URBAN RAIL TRAIN OPERATION STRATEGY OPTIMIZATION

Kaiwei Liu, Xingcheng Wang and Longda Wang

School of Marine Electrical Engineering
Dalian Maritime University
No. 1, Linghai Road, Dalian 116026, P. R. China
dmuwxc@dlmu.edu.cn

Received April 2019; revised August 2019

Abstract. *The problem to be solved for the urban rail train operation strategy optimization is to find an optimal solution which can take account of various optimization indexes. Therefore, the multi-objective optimization model for the urban rail train operation is established with energy consumption, punctuality, comfort level and parking precision as optimization indexes. An improved Memetic Algorithm (MA) is used to solve the multi-objective optimization model under the operating constraints. In the framework of MA, its global search strategy adopts Genetic Algorithm (GA), and its local search strategy uses the predatory search mode based on the urban rail train's own characteristics. In GA, the convergence rate of the algorithm is improved by adjusting the selection pressure adaptively according to the number of iterations. Besides, to avoid MA falling into the local optimum in the optimization process as far as possible, the dynamic Opposition-Based Learning (OBL) mechanism is adopted to produce the opposite population, which expands the global search scope. The simulation results show that the improved MA has better optimization performance, compared with the classical MA and GA.*

Keywords: Urban rail train, Memetic algorithm, Genetic algorithm, Opposition-based learning, Multi-objective optimization

1. Introduction.

The urban rail train operation is a complicated control process which needs to satisfy multiple performance indexes such as safety, energy saving, punctuality, parking precision and comfort level, and these performance indexes are influencing each other [1,2]. Besides, the urban rail train operation strategy optimization is that the best one among many feasible urban rail train operating strategies is chosen under the given line constraints [3,4]. It is necessary to establish the multi-objective optimization model for the urban rail train to obtain a better train operating strategy.

For now, a large number of methods have been applied to the multi-objective optimization of the urban rail train operating process, such as GA, fuzzy predictive control, Particle Swarm Optimization (PSO), and linear programming method. In [5], aiming at the multi-objective optimization strategy of the train, an improved GA is proposed, in which the penalty function is added to the fitness objective function to improve the convergence speed of GA. At the same time, the five performance indexes are considered, namely, safety, parking accuracy, punctuality, energy consumption and comfort. In [6], the structure and function of Automatic Train Operation (ATO) system are analyzed in detail, and the fuzzy predictive control for ATO speed tracking system is designed by combining fuzzy logic and predictive control. The simulation results show that the performance indexes such as safety, comfort and parking accuracy have been significantly improved. In [7], a robust optimization technique based on multi-objective PSO is

DOI: 10.24507/ijicic.16.01.241

proposed for ATO system, and an optimal pareto front with robust ATO velocity distribution is constructed, which considers two performance indexes of running time and energy consumption. Besides, the use of statistical information about delays provides additional energy savings between 3% and 14%. In [8], an efficient and energy-saving train operating model based on real-time traffic information is built by using the method of the linear programming, and the energy saving operating strategy is derived by combining analysis and numerical value. In this way, the delayed trains can be kept on time at the next station and the energy consumption can be reduced. In [9], aiming at the problem of energy saving and efficient operation for subway trains, a bi-level programming model of multiple interstations is established. And the Multi-Population Genetic Algorithm (MPGA) is used to solve the model, followed by calculating the energy-efficient trip times. Comparing with only optimizing the driving strategy for a single interstation, the proposed method has better searching performance. In [10], the multi-objective optimization model for the train operation adjustment is established, whose optimization objective is to reduce the delay time of the train and the numbers of delay train. Considering the dispatcher's preferred strategy, a Multi-objective Particle Swarm Optimization (MPSO) algorithm is used to obtain a set of Pareto solutions.

References [5-10] have made great contributions to the multi-objective optimization of urban rail train operation process, but there is no denying that the better results may be also achieved by using other optimization algorithms. MA is an optimization algorithm based on simulated cultural evolution proposed by Pablo Moscato, and it is a combination of the global search and local heuristic search [11]. In [12], aiming at the multi-objective optimization model under real-time electricity price, an adaptive multi-objective MA is proposed, and the crossover advantage and stagnation feedback are introduced into the search and priority grouping strategy. In addition, an adaptive balance also needs to be maintained between the exploration of NSGA-II and the two complementary local searches. In [13], for the vehicle routing problem with route balancing, a Multi-objective Memetic Algorithm (MMA) is proposed, which integrates the local search process into the multi-objective evolutionary algorithm. And MMA is further improved by parallel computing. In [14], an improved MA is proposed by integrating a general multi-objective evolutionary algorithm (NSGA-II) and a problem-specific heuristic (NEH) for two optimization objectives of shop scheduling. NEH is taken as an improved program of MA, and better optimization effect is achieved. Therefore, in this paper, MA is adopted to search the urban rail train operation strategy. GA is an optimization algorithm developed by simulating the evolution of natural species, and it has strong global search ability [15]. So, the global search strategy of MA adopts GA, and the optimization performance of the algorithm is improved by adjusting the selection pressure adaptively according to the number of iterations. In addition, predatory search algorithm is a bionic computing method that simulates animal predatory strategy proposed by Linhares Alexandre in 1998, and it has strong local search ability. Inspired by the predatory search strategy, the local search strategy of MA adopts the predatory search mode based on the urban rail train's own characteristics. In order to expand the search scope of the MA, the OBL mechanism is used to generate the opposite population according to the current population [16]. The current population and opposite population are combined for the selection of the offspring population.

This paper is organized as follows. Section 2 describes the operation conditions for urban rail train. In Section 3, the multi-objective optimization model for urban rail train is built, and the entropy weight method is used to weight all the indexes. In Section 4, an improved MA is proposed to solve the multi-objective optimization model for urban rail train under the operating constraints. In Section 5, MATLAB simulation results show that the improved MA has better optimization performance. The conclusion is described in Section 6.

2. Problem Description for the Urban Rail Train.

2.1. The operating conditions of the urban rail train. According to the principle of energy-saving operation for urban rail train, it starts with the maximum traction, stops with the maximum braking force, and maintains coasting operation or constant speed state during the running process as far as possible, which can reduce energy consumption to the greatest extent. Therefore, the operating conditions for urban rail train are divided into the maximum traction (which is represented by 1), the maximum braking (-1), the coasting operation (0) and the constant speed state (0.1). The coasting operation state represents that the urban rail train exerts no traction or braking force. When the urban rail train travels in the same section, the operating results obtained by different operating conditions are different. In this paper, taking the operating conditions and the switching positions corresponding to the operating conditions as the decision variables (the train control sequence), MA is used to solve the multi-objective optimization model of the urban rail train. To describe the decision variables more clearly, take Figure 1 for example.

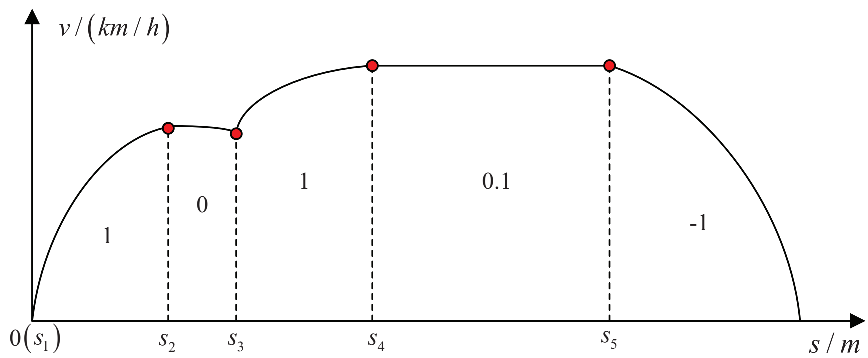

FIGURE 1. Schematic diagram for the urban rail train operation

In Figure 1, the urban rail train starts by using the maximum traction (1) from s_1, switches to '0' operating condition at s_2, accelerates by using '1' operating condition at s_3, then switches to '0.1' operating condition at s_4, finally slows down by using '-1' operating condition until it stops. $\{(s_1, 1), (s_2, 0), (s_3, 1), (s_4, 0.1), (s_5, -1)\}$ is a decision variable, that is, an urban rail train control sequence.

2.2. Design of the initial operating conditions. In order to avoid the blind search of MA, before solving the multi-objective optimization model of urban rail train operation, the initial operating conditions are obtained according to the interval line conditions, especially the speed limit. Any complex speed limit interval can be divided into three speed limit subintervals, namely, the no static speed limit falling interval, the static speed limit falling interval, the static speed limit falling and rising interval. The initial operating conditions of the three speed limiting subintervals are shown in Figure 2.

In Figure 2, the urban rail train control sequences of the three speed limiting subintervals are $u_1 = \{(s_1, 1), (s_2, 0), (s_3, 1), (s_4, 0.1), (s_5, 0), (s_6, -1)\}$, $u_2 = \{(s_1, 1), (s_2, 0), (s_3, -1), (s_4, 0.1), (s_5, 1), (s_6, 0), (s_7, -1)\}$ and $u_3 = \{(s_1, 1), (s_2, 0), (s_3, 1), (s_4, 0), (s_5, -1), (s_6, 0.1), (s_7, 1), (s_8, 0), (s_9, -1)\}$, respectively. When the urban rail train keeps coasting condition (0) or constant speed condition (0.1), the energy consumption is the least. The initial operating conditions of the three speed limiting subintervals fully follow

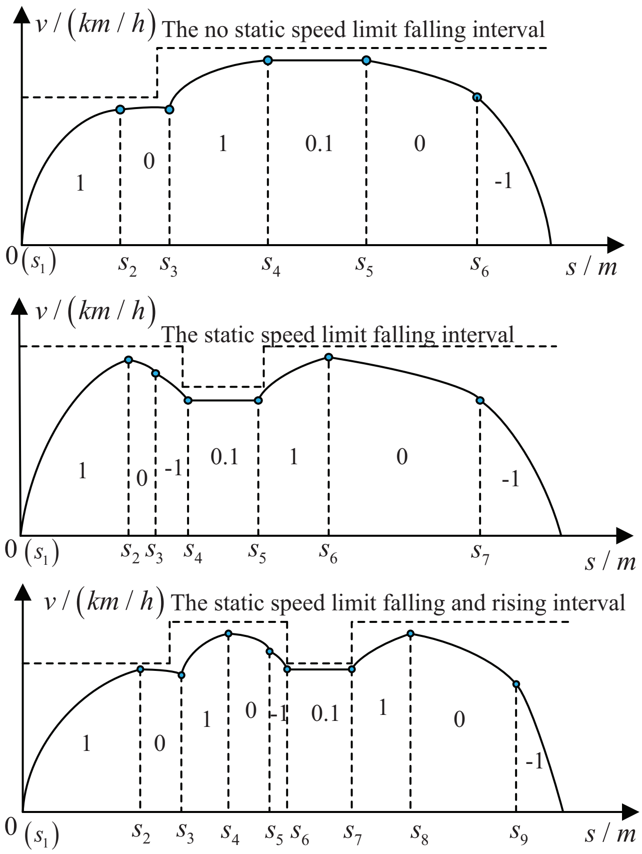

FIGURE 2. The initial operating conditions of the three speed limiting subintervals

the energy minimum principle, which can reduce the energy consumption to the greatest extent. Taking u_1 as an example, u_1 is a chromosome which adopts the coding mechanism of the real number, and $(s_1, 1)$ is a gene in u_1. For any given interval, the number of genes in the chromosome is fixed, that is, the length of the chromosome is fixed.

3. Operating Model for Urban Rail Train.

3.1. Urban rail train dynamic model.

The differential equation of urban rail train motion and constraint condition are

$$\begin{cases} \dfrac{dt}{ds} = \dfrac{1}{v} \\ (1+\gamma)Mv\dfrac{dv}{ds} = f(u,v) - w(s,v) - b(u,v) \end{cases} \tag{1}$$

$$\text{s.t.} \begin{cases} v(0) = v(S) = 0 \\ v(s) \le v_{\lim}(s), \ \ s \in [0, S] \end{cases} \tag{2}$$

where M is the mass of the urban rail train; γ is the rotary mass coefficient; $f(u,v)$ is the actual traction of the urban rail train, which is determined by the control sequence u and the actual running speed v of the urban rail train; $w(s,v)$ is the resistance of the urban rail train, which is determined by v and the actual position s of the urban rail train; $b(u,v)$ is the braking force of the urban rail train, which is determined by u and v; $v(0)$ and $v(S)$ are the initial and final speeds of the urban rail train; S is the actual distance between the two stations; $v(s)$ and $v_{\lim}(s)$ are the actual speed and restricted speed of the urban rail train at the position s.

3.2. **Multi-objective optimization model for urban rail train.** The urban rail train operation strategy optimization is a complex multi-objective optimization problem that needs to take into account multiple performance indexes such as safety, punctuality, energy saving, comfort level and parking precision at the same time. These optimization indexes influence each other, and the importance of each index is not the same in the process of the urban rail train operation. Therefore, in this paper, taking energy consumption, punctuality, comfort level and parking precision as optimization indexes, the multi-objective optimization model of the urban rail train operation strategy is built.

(i) The calculation model of energy consumption index for the urban rail train operation is

$$E = \frac{\int Fvdt}{\xi_M} + AT + \xi_B \int Bvdt \tag{3}$$

where E is the energy consumed by the urban rail train; F and B are the traction force and braking force; A is the auxiliary power of the urban rail train; T is the actual running time of the urban rail train between two stations; ξ_M is the conversion factor that converts electrical energy into mechanical energy during the urban rail train pulling; ξ_B is the conversion factor that converts mechanical energy into electrical energy during the urban rail train braking.

(ii) The calculation model of the comfort level index for the urban rail train operation is

$$Q = \sum_{i=2}^{N} |a_i - a_{i-1}| \tag{4}$$

where a_i and a_{i-1} are the accelerations of the two adjacent sampling points.

(iii) The calculation model of the parking precision index for the urban rail train operation is

$$P = |S - S_{actual}| \tag{5}$$

where S is the distance between the two stations; S_{actual} is the actual running distance of the urban rail train between the two stations. According to the regulation of the urban rail train, P cannot exceed 30 cm, so that passengers can get on and off the train normally.

(iv) The calculation model of the punctuality index for the urban rail train operation is

$$\Delta T = \left| \sum_{i=1}^{N} T_i - T_{set} \right| \tag{6}$$

where the whole interval is evenly divided into N cells; T_i is the running time in each cell $(i = 1, \ldots, N)$; T_{set} is the pre-set running time between two stations.

Based on E, Q, P and ΔT, the multi-objective optimization model of the urban rail train operation can be obtained as follows.

$$\min \quad G\big(E, \quad Q, \quad P, \quad \Delta T\big) \tag{7}$$

where G is the optimization objective function; min is used to minimize G.

In addition, the multi-objective optimization problem can be transformed into the single-objective optimization problem by the weighted sum method. Therefore, the optimization function G is processed as follows.

$$G = \omega_1 E + \omega_2 Q + \omega_3 P + \omega_4 \Delta T \tag{8}$$

ω_1, ω_2, ω_3 and ω_4 are respectively the weight coefficients of the four optimization indexes $(E, Q, P, \Delta T)$.

3.3. **Entropy weight method.** Entropy is originally a thermodynamic concept, and it is first introduced by C. E. Shannon to the information theory, called information entropy. C. E. Shannon has proved the following conclusion.

If the information entropy of an index is smaller, it indicates that this index has a greater degree of variation and provides more information. The more important this index is in the comprehensive evaluation, the greater its weight will be. On the contrary, if the information entropy of an index is larger, it indicates that this index has less degree of variation and provides less information. This index plays a smaller role in the comprehensive evaluation and its weight is also smaller.

Therefore, in this paper, the entropy weight of the four performance indexes for the urban rail train can be calculated by information entropy according to the variation degree of each index. Then all indexes are weighted by entropy weight to get objective evaluation results. The specific steps of entropy weight method are as follows.

(i) Data standardization

For m evaluation indexes, n sets of data are taken to construct the evaluation matrix $X_{n\times m}$ as follows.

$$X_{n\times m} = \begin{bmatrix} X11 & X12 & \cdots & X1m \\ X21 & X22 & \cdots & X2m \\ \cdots & \cdots & \cdots & \cdots \\ Xn1 & Xn2 & \cdots & Xnm \end{bmatrix} \tag{9}$$

Equation (9) is normalized to obtain the normalized evaluation matrix $R_{n\times m}$, and each element R_{ij} in $R_{n\times m}$ is

$$R_{ij} = \frac{Xij - \min\limits_i(Xij)}{\max\limits_i(Xij) - \min\limits_i(Xij)} \tag{10}$$

(ii) The information entropy of each index

According to the definition of information entropy in information theory, the information entropy E_j of the jth optimization index is

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{11}$$

where $p_{ij} = R_{ij} \Big/ \sum\limits_{i=1}^{n} R_{ij}$ $(i = 1, \ldots, n \quad j = 1, \ldots, m)$. If $p_{ij} = 0$, then $p_{ij} \ln p_{ij} = 0$.

(iii) The weight of each index

According to Equation (11) for information entropy, the information entropy of each optimization index is

$$E_1, E_2, \ldots, E_m \tag{12}$$

Then, the entropy weight of each index is calculated as

$$W_i = \frac{1 - E_j}{m - \sum\limits_{j=1}^{m} E_j} \tag{13}$$

For four optimization indexes $(E, Q, P, \Delta T)$ of the urban rail train, in this paper, 25 sets of data are taken to form the normalized evaluation matrix $R_{n\times m}$ $(m = 4,\ n = 25)$. After the calculation, the weight ω_1 of E is 0.4219, the weight ω_2 of Q is 0.2856, the weight ω_3 of P is 0.1964, and the weight ω_4 of ΔT is 0.0961.

4. **Urban Rail Train Operation Strategy Optimization Based on Improved MA.** The MA was first proposed by Pablo Moscato in 1989. In fact, the MA proposes a framework, a concept, which can be defined as the collaboration between global population evolution and local individual learning [17]. In this framework, different search strategies can be used to construct different memetic algorithms. In the paper, the global search strategy of MA uses GA, and the local search strategy of MA uses the predatory search mode based on the urban rail train's own characteristics. In addition, to avoid MA falling into the local optimum in the optimization process as far as possible, the dynamic OBL mechanism is adopted to produce the opposite population, which enlarges the search scope.

4.1. **Global search strategy using GA.** GA is an optimization algorithm developed by simulating the evolution of natural species. Based on the principle of biological evolution, it simulates natural genetic processes such as crossover and mutation. New populations are generated by simulating the process of natural selection. The essence of GA is an efficient global search algorithm. So, the global search strategy for MA uses GA. The GA includes selection operator, crossover operator and mutation operator, and three genetic operators are designed as follows.

4.1.1. *Selection operator based on adaptive change of selection pressure.* The function of the selection operator is to select some chromosomes from the parent population into the offspring population for evolution. All chromosomes of the parent population need to be sorted before the selection operator is performed. So, this paper adopts the linear sorting method based on adaptive change of selection pressure for selection operator. Firstly, all chromosomes in the population are sorted from largest to smallest according to their fitness function values, and the sorted chromosomes are shown in Equation (14). Then, each chromosome u_j in the population is assigned a selected expected value p according to the rules of the linear sorting method, and the calculation formula of p is shown in Equation (15).

$$U = \{u_1, u_2, \ldots, u_n\} \tag{14}$$

$$p(u_j) = \frac{1}{n}\left[(2 - pre) + \frac{2(pre - 1)(j - 1)}{n - 1}\right] \tag{15}$$

where U is a population; n is the population size; u_j is the jth chromosome ($j = 1, 2, \ldots, n$); pre is the parameter related to the selection pressure; when $pre = 0$, the selection pressure is maximum, and the probability that the worst individual survives is 0. When $pre = 1$, the selection pressure is the minimum, and the individuals of the parent population are randomly selected.

Therefore, according to the number of iterations, the selection pressure can be adjusted adaptively to select the offspring individuals. At the early stage of the iteration, the individual differences in the population are large, so the selection pressure is lower to avoid the loss of population diversity. At the later stage of the iteration, the individual differences in the population become smaller, so the selection pressure is higher to find the optimal solution. The selection pressure increases as the number of the iterations increases, which is as follows.

$$pre = 1 - k/k_{\max} \tag{16}$$

where k represents the current iterative number; $k_{\max}$ is the maximum iterative number. The selection pressure is inversely proportional to the value of pre.

After the linear sorting, the chromosomes in the parent population need to be selected into the offspring population by means of the roulette, which is shown in Figure 3.

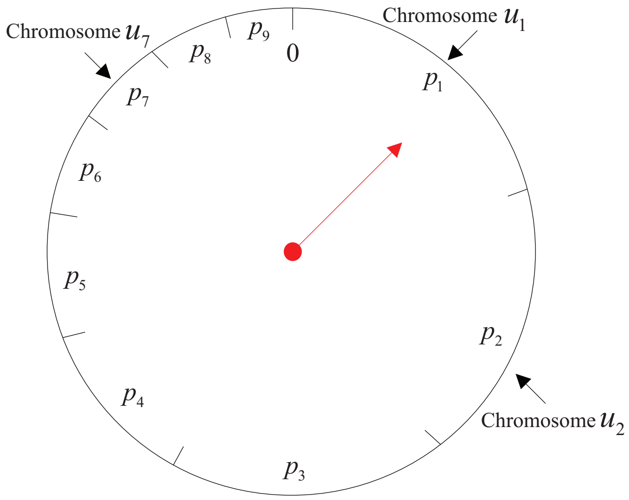

FIGURE 3. The diagram of the roulette selection

In Figure 3, taking 9 chromosomes for example, the pointer on the wheel turns randomly to generate a random number a between 0 and 1. If $p_1 < a \leq p_1 + p_2$, the chromosome u_2 is selected. The wheel needs to be turned 9 times to get 9 new chromosomes.

4.1.2. *Crossover operator based on the linear reorganization.* The crossover operator is designed by the linear recombination method. Before performing the crossover operation, the 8 genes from the two chromosomes (two train control sequences) to be crossed are selected as the crossover points. The linear combination is conducted for the switching positions of the operating conditions in the crossover points according to Equation (17), and the operating conditions in the crossover points are interchanged, which is shown in Figure 4.

$$\begin{cases} {s_1}' = (1-\alpha)s_1 + \alpha s_2 \\ {s_2}' = (1-\alpha)s_2 + \alpha s_1 \end{cases} \tag{17}$$

where s_1 and s_2 are the switching positions of the operating conditions in the crossover points of the two chromosomes to be crossed; ${s_1}'$ and ${s_2}'$ are the switching positions of the operating conditions in the crossover points of the two new chromosomes; α is a random number between 0 and 1.

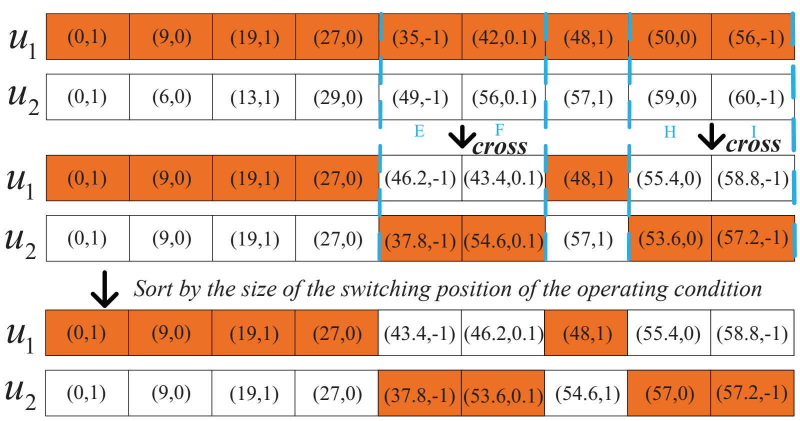

FIGURE 4. The diagram of the crossover operator

In Figure 4, E, F, H and I are the selected crossover points. u_1 and u_2 are the two chromosomes that are used to perform the crossover operation, and they are represented by two different colors. Since the train control sequence is sorted in ascending order according to the size of the switching position of the operating condition, after the crossover operation, the original control sequence may be disrupted. So, the new chromosomes need to be reordered according to the size of the switching position of the operating condition.

4.1.3. *Mutation operator using the multi-point mutation.* Before the mutation operation is performed, three genes are randomly selected as the mutation points in the chromosome to be mutated. Linear combination is conducted according to Equation (18) for the switching positions of the two operating conditions before and after the mutation point to obtain the new switching positions of the operating conditions, which is shown in Figure 5.

$$s_i' = \beta s_{(i-1)} + (1-\beta)s_{(i+1)} \tag{18}$$

where s_i is the switching position of the operating condition in the mutation point of the chromosome to be mutated; s_i' is the switching position of the operating condition in the mutation point of the new chromosome after the mutation operation; $s_{(i-1)}$ and $s_{(i+1)}$ are the switching positions of the two operating conditions before and after the mutation point; β is a random number between 0 and 1.

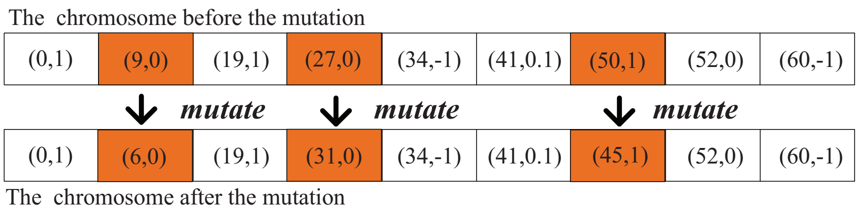

FIGURE 5. The diagram of the mutation operator

In Figure 5, there are three mutation points. The mutation operation only changes the switching position of the operating condition, but not the operating condition.

4.2. **Local search strategy based on the predatory search.** In the framework of MA, although GA has strong global search ability, its local search ability is weak. So, a local search strategy based on the idea of the predatory search is designed. The idea of the predatory search is as follows: First, search for feasible solutions in the whole solution space, and change the search mode and strategy once a suboptimal solution is found somewhere; then, search around the suboptimal solution; if a better solution cannot be found, continue searching until it is found. Inspired by the predator search, the predatory search strategy based on the urban rail train's own characteristics is proposed.

The local search strategy takes the following approach: the kth chromosome in the process of population evolution is called u_k, and the optimization functions of u_k in the mth generation and the $(m-1)$th generation are $G_m(u_k)$, $G_{m-1}(u_k)$. If $G_m(u_k) > G_{m-1}(u_k)$, the local search is not performed. If $G_m(u_k) < G_{m-1}(u_k)$, it indicates that the evolution direction of the mth generation of the chromosome u_k is better, and the local search is started. At this point, for the genes of chromosomes u_k in the mth generation and the $(m-1)$th generation, there are three cases that can occur in the local search.

Case1: The switching position of the operating condition for a gene of the chromosome u_k in the mth generation is backward compared with that in the $(m-1)$th generation, which is shown in Figure 6.

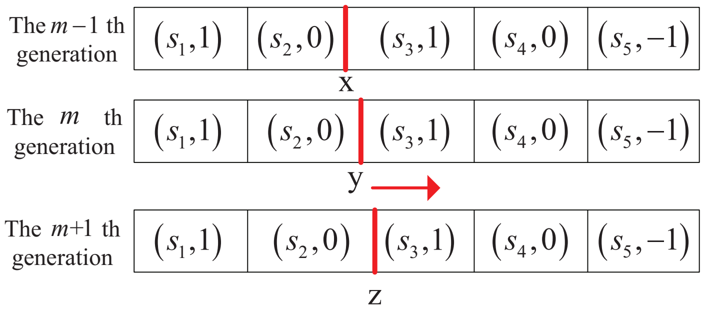

FIGURE 6. The backward switching position of the operating condition

In Figure 6, since the position s_3 in the gene $(s_3, 1)$ moves from x to y, the position s_3 in the gene $(s_3, 1)$ of the $(m + 1)$th generation needs to move from y to z.

Case2: The switching position of the operating condition for a gene of the chromosome u_k in the mth generation is forward compared with that in the $(m + 1)$th generation, which is shown in Figure 7.

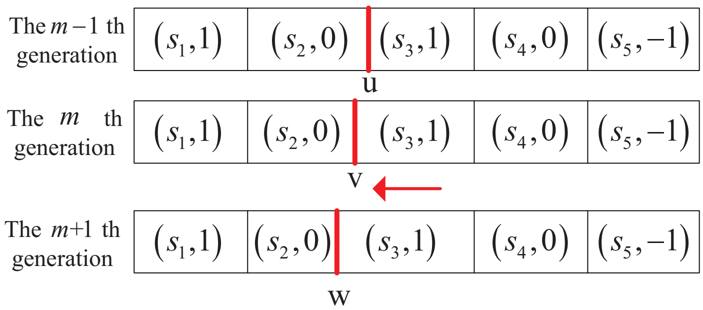

FIGURE 7. The forward switching position of the operating condition

In Figure 7, since the position s_3 in the gene $(s_3, 1)$ moves from u to v, the position s_3 in the gene $(s_3, 1)$ of the $(m + 1)$th generation needs to move from v to w.

Case3: The operating condition for a gene of the chromosome u_k in the mth generation changes compared with that in the $(m - 1)$th generation, which is shown in Figure 8.

In Figure 8, the operating condition in the gene $(s_3, 1)$ changes from '1' to '0.1'. So, the position s_3 of the gene $(s_3, 0.1)$ of the $(m+1)$th generation needs to be randomly generated

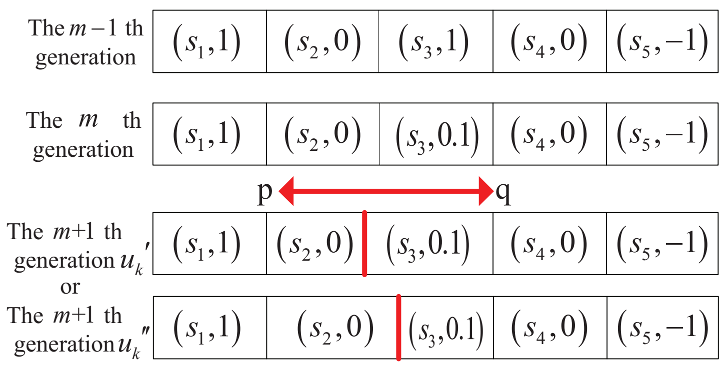

FIGURE 8. The change of the operating condition

within the range of p to q. s_3 might move forward, as shown on the chromosome $u_k{}'$. s_3 could also move backward, as shown on the chromosome $u_k{}''$.

4.3. **The MA based on the OBL mechanism.** The concept of OBL was proposed by Tizhoosh in 2005, and he explained that the opposite solution was 50% more likely to approach the global optimal solution than the current solution. The main idea of OBL is that the opposite individuals are generated based on the current individuals. Then the opposite individuals and the current individuals participate in the competition at the same time, and the excellent individuals are reserved for the next generation. The OBL mechanism is defined as follows.

Definition 4.1 (**Opposite solution**). *Let a feasible solution in N-dimensional search space be $x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{iN})$, $x_{ij} \in [a_j, b_j]$, $j \in [1 : N]$. And let the opposite solution be $x_i{}' = (x_{i1}{}', x_{i2}{}', x_{i3}{}', \ldots, x_{iN}{}')$, which satisfies Equation (19).*

$$x_{ij}{}' = a_{ij} + b_{ij} - x_{ij} \tag{19}$$

Definition 4.2 (**Generalized opposite solution**). *Let $x_{ij}{}' = k\,(a_j + b_j) - x_{ij}$ be the generalized opposite solution, where $x_{ij} \in [a_j, b_j]$, $i = 1, 2, \ldots, pop$, $j = 1, 2, \ldots, N$. pop is the population size, and N is the dimension of the search space. k in Definition 4.2 can take on different numbers. When $k = 0$, $x_{ij}{}'$ is a generalized OBL based on the symmetry solution; when $k = 0.5$, $x_{ij}{}'$ is a generalized OBL based on the symmetry interval; when $k = 1$, $x_{ij}{}'$ is a generalized OBL; when k is a random number between 0 and 1, $x_{ij}{}'$ is a stochastic generalized OBL.*

Definition 4.3 (**General dynamic OBL**). *Let $x_{ij}{}' = k\,(a_j{}' + b_j{}') - x_{ij}$ be the general dynamic opposite solution, where $a_j{}'$ and $b_j{}'$ are the minimum and maximum values in the jth dimension of the current search space.*

$$\begin{cases} a_j{}' = \min\,(B_j) \\ b_j{}' = \max\,(B_j) \end{cases} \tag{20}$$

where B_j is the set of all the values in the jth dimension of all the individuals in the current population; $k \in [0, 1]$ is the factor of the general dynamic OBL.

The experiment results show that the third definition is more effective, so the third definition is applied to the MA. The general dynamic OBL strategy is shown in Figure 9.

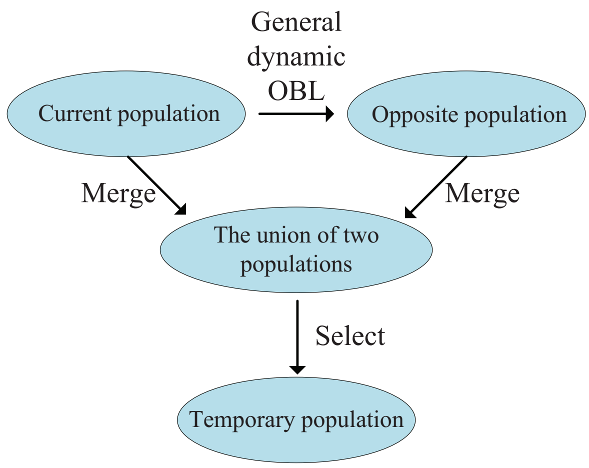

FIGURE 9. The diagram of the general dynamic OBL

In Figure 9, the opposite population is generated by using the general dynamic OBL strategy according to the current population. Next, the current population and the opposite population are merged into a union. Then, the excellent individuals are chosen from the union to form a temporary population, whose size is the same as the current population size. Finally, the temporary population is used for selection, crossover and mutation operations. The advantage of the general dynamic OBL mechanism is that it not only expands the search scope but also avoids invalid search, so that the individuals can converge to the global optimal solution more quickly.

Finally, the flow chart of IMA for the urban rail train operation strategy optimization is shown in Figure 10.

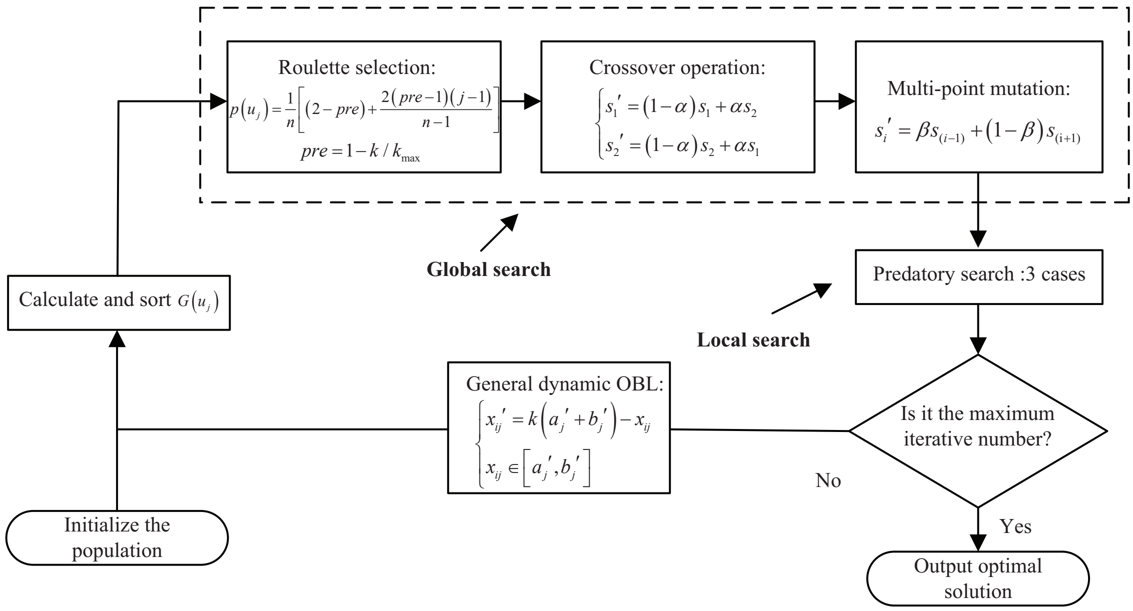

FIGURE 10. The flow chart of IMA

5. The Experimental Simulation.

5.1. Relevant data of train. This paper selects the urban rail train of Jinpu line 1 in Dalian as the research object, and two sections are selected as the experimental line. The basic parameters of the urban rail train are shown in Table 1, and the slope attributes and the speed limit attributes of the line are shown in Figure 11.

TABLE 1. The basic parameters of the urban rail train

Parameter name	Parameter characteristics
Train weight (t)	209
Maximum running speed (km/h)	80
Formation plan	2 motor 2 trail
Mean starting acceleration (m/s^2)	(0∼35 km/h) $\geq$ 1.0
Mean acceleration (m/s^2)	(0∼80 km/h) $\geq$ 0.6
Mean braking deceleration (m/s^2)	(80∼0 km/h) $\geq$ 1.0
Rotary mass coefficient (γ)	0.06

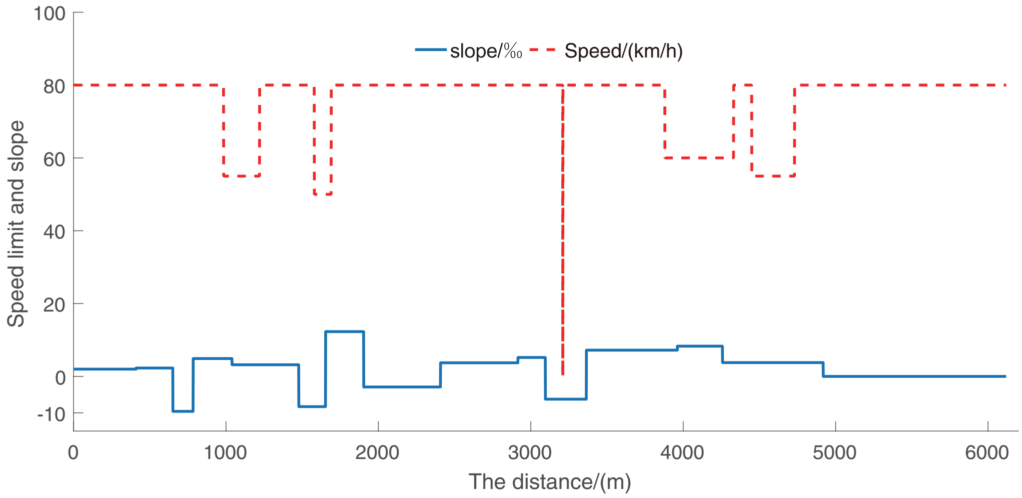

FIGURE 11. The slope attributes and the speed limit attributes of the line

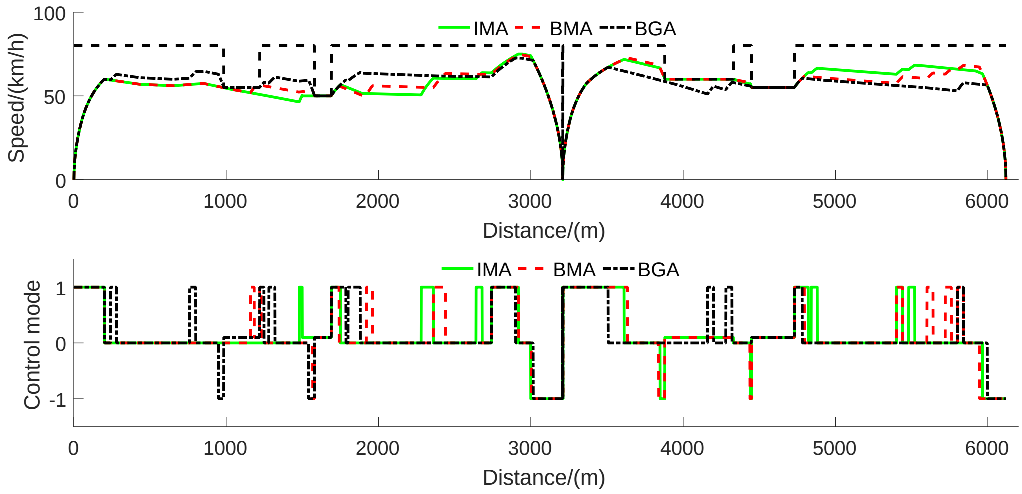

FIGURE 12. The velocity distance curves and the control sequences obtained by different algorithms $\left(\tilde{T} \in [401\, s, 404\, s]\right)$

5.2. **Multi-objective optimization results of the urban rail train operation process.** Based on MATLAB simulation environment, the Basic Genetic Algorithm (BGA), the Basic Memetic Algorithm (BMA) and the Improved Memetic Algorithm (IMA) are used to solve the multi-objective optimization model of the urban rail train operation process respectively for the Jinpu line 1. For BMA, its local search strategy adopts B-GA, and its global search strategy adopts Hill Climbing Algorithm (HCA). The optimal curves by different algorithms are shown in Figures 12-14, and the optimization results obtained by different algorithms are shown in Tables 2-4, including energy consumption, punctuality, comfort level, switching number of operation condition (which is also called frequency) and parking error. This paper selects 3 pre-set times (401 s, 414 s and 432 s), where $\tilde{T}$ is the actual running time of the urban rail train.

In Figures 12-14, IMA enables the urban rail train to maintain the appropriate speed more smoothly. For the control sequences obtained by IMA, the proportion of the time

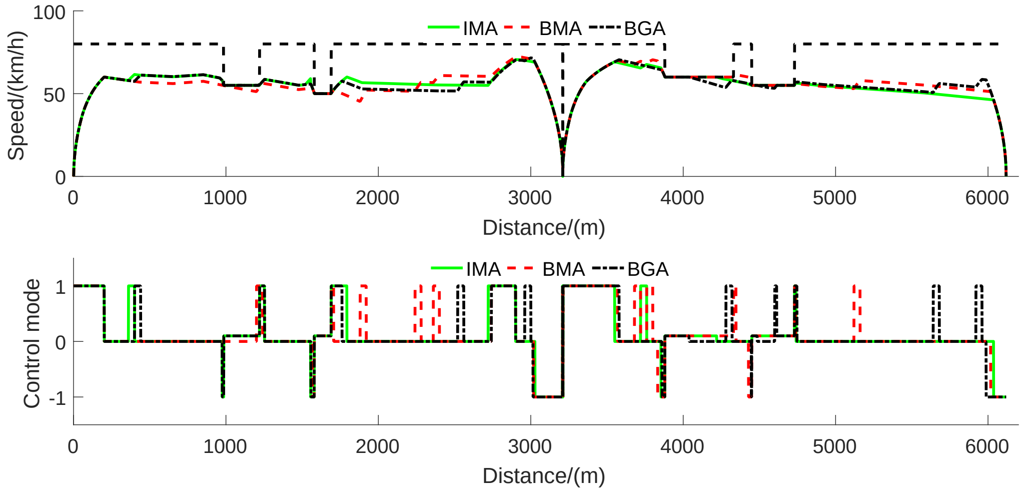

FIGURE 13. The velocity distance curves and the control sequences obtained by different algorithms $\left(\tilde{T} \in [414\,s, 417\,s]\right)$

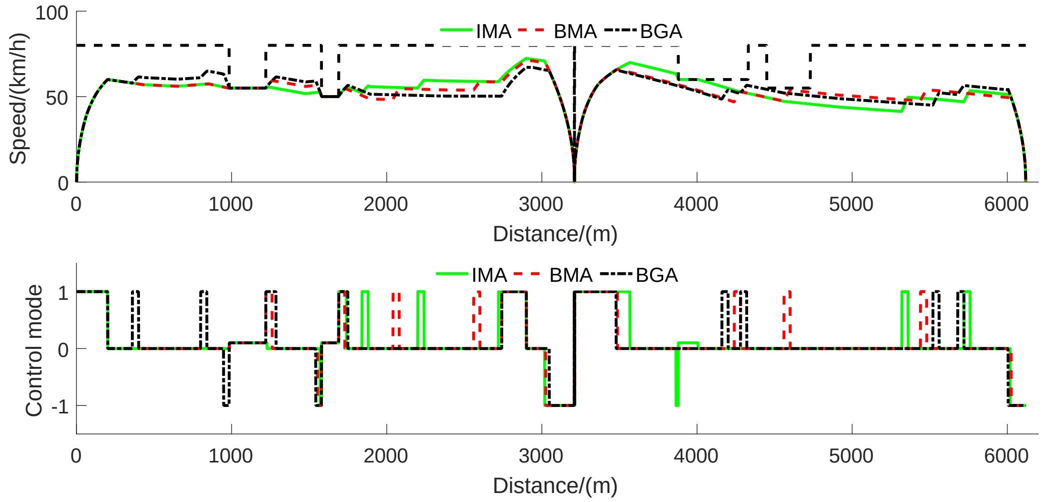

FIGURE 14. The velocity distance curves and the control sequences obtained by different algorithms $\left(\tilde{T} \in [432\,s, 435\,s]\right)$

TABLE 2. The optimization results obtained by different algorithms $\left(\tilde{T} \in [401\,s, 404\,s]\right)$

Algorithm	Energy consumption	Punctuality	Comfort level	Frequency	Parking error
IMA	211546 KJ	0.912 s	35.72 m/s^2	29	0.23 m
BMA	219547 KJ	1.210 s	40.89 m/s^2	35	0.36 m
BGA	230214 KJ	1.654 s	45.10 m/s^2	33	0.41 m

consumed by the coasting condition (0) and the constant speed condition (0.1) is relatively large, and the conversion frequency of the traction and braking condition is also less, which can save energy consumption and improve passengers' comfort. Compared with BMA and BGA, when the pre-set time is large, IMA can keep the train in the coasting condition

TABLE 3. The optimization results obtained by different algorithms $\left(\tilde{T} \in [414\,s, 417\,s]\right)$

Algorithm	Energy consumption	Punctuality	Comfort level	Frequency	Parking error
IMA	182135 KJ	1.112 s	32.54 m/s^2	26	0.14 m
BMA	199854 KJ	1.812 s	38.24 m/s^2	34	0.22 m
BGA	209754 KJ	1.998 s	41.45 m/s^2	38	0.33 m

TABLE 4. The optimization results obtained by different algorithms $\left(\tilde{T} \in [432\,s, 435\,s]\right)$

Algorithm	Energy consumption	Punctuality	Comfort level	Frequency	Parking error
IMA	152461 KJ	1.333 s	29.54 m/s^2	25	0.14 m
BMA	156542 KJ	2.002 s	35.61 m/s^2	25	0.25 m
BGA	164587 KJ	2.105 s	37.68 m/s^2	28	0.27 m

(0.1) as far as possible on the long straight track, which is as shown in Figure 14. When the preset time is small, IMA enables the urban rail train to accelerate in a reasonable manner timely, thus avoiding unnecessary traction and braking conditions to the greater extent, which is as shown in Figure 13. Obviously, the control sequence obtained by IMA is conducive to energy saving and avoiding turbulence.

In Table 2, the energy consumption obtained by IMA is 3.64% and 8.11% lower than that of BMA and BGA, and the punctuality index obtained by IMA is 24.63% and 44.86% higher than that of BMA and BGA. In Table 3, the energy consumption obtained by IMA is 8.87% and 13.17% lower than that of BMA and BGA, and the punctuality index obtained by IMA is 38.63% and 44.34% higher than that of BMA and BGA. In Table 4, the energy consumption obtained by IMA is 2.61% and 7.37% lower than that of BMA and BGA, and the punctuality index obtained by IMA is 33.42% and 36.67% higher than that of BMA and BGA. Therefore, for different pre-set times, the punctuality index obtained by IMA has particularly great improvement, up to 44.86%. The energy consumption index obtained by IMA has also improved, not as much as the punctuality index. In Tables 2-4, as the pre-set time $\tilde{T}$ increases (the average speed decreases), the energy consumption obtained by different algorithms decreases obviously. Besides, the switching number of the operation conditions for the control sequence obtained by IMA is the least, which can greatly improve the passengers' comfort level. Under the different pre-set times, compared with BMA and BGA, the comfort index obtained by IMA is better and the parking error obtained by IMA is lower.

Therefore, the simulation results verify that IMA has better optimization performance for the urban rail train operation strategy optimization.

6. **Conclusions.** MA is a swarm intelligence optimization algorithm with strong search ability, which is suitable for solving the complex engineering practical problem such as the urban rail train operation process optimization. However, the convergence rate of the basic MA is slow, and it tends to fall into the local optimality. Therefore, in this paper, an improved MA for the urban rail train operation strategy optimization is proposed. Since GA has a strong global ability, GA is adopted as the global search strategy of MA. And the convergence rate of GA can be accelerated by adjusting the selection pressure adaptively according to the number of iterations. Besides, the local search strategy of MA adopts the predatory search based on the urban rail train's own characteristics, which greatly improves the optimization performance of MA. Finally, the general dynamic OBL

mechanism is introduced into MA produce to the opposite population, which can expand the search scope and avoid local convergence.

There are many kinds of frameworks for MA, and only one of them is deeply studied in this paper to achieve good results. To achieve better results, the research on various frameworks for MA is needed in the future.

Acknowledgment. This research is supported by National Natural Science Foundation of China (60574018).

REFERENCES

[1] S. Watanabe, T. Koseki and E. Isobe, Evaluation of automatic train operation design for energy saving based on the measured efficiency of a linear-motor train, *Electrical Engineering in Japan*, vol.202, no.4, pp.460-468, 2018.

[2] Z. Miao, Y. Wang and S. Shuai, A short turning strategy for train scheduling optimization in an urban rail transit line: The case of Beijing subway line 4, *Journal of Advanced Transportation*, vol.2018, pp.1-19, 2018.

[3] T. Zhang, D. Li and Q. Yu, Comprehensive optimization of urban rail transit timetable by minimizing total travel times under time-dependent passenger demand and congested conditions, *Applied Mathematical Modelling*, vol.58, pp.421-446, 2018.

[4] G. Wang, S. Xiao and C. Xi, Application of genetic algorithm in automatic train operation, *Wireless Personal Communications*, vol.102, no.2, pp.1695-1704, 2018.

[5] Y. Liang, H. Liu and C. Qian, A modified genetic algorithm for multi-objective optimization on running curve of automatic train operation system using penalty function method, *International Journal of Intelligent Transportation Systems Research*, 2018.

[6] Y. Cao, L. Ma and Y. Zhang, Application of fuzzy predictive control technology in automatic train operation, *Cluster Computing*, 2018.

[7] A. Fernandez-Rodriguez, A. Fernandez-Cardador and A. P. Cucala, Design of robust and energy-efficient ATO speed profiles of metropolitan lines considering train load variations and delays, *IEEE Transactions on Intelligent Transportation Systems*, vol.16, no.4, pp.2061-2071, 2015.

[8] Q. Gu, T. Tang and F. Cao, Energy-efficient train operation in urban rail transit using real-time traffic information, *IEEE Transactions on Intelligent Transportation Systems*, vol.15, no.3, pp.1216-1233, 2014.

[9] H. Youneng, M. Xiao and S. Shuai, Optimization of train operation in multiple interstations with multi-population genetic algorithm, *Energies*, vol.8, no.12, pp.14311-14329, 2015.

[10] L. Hang, Y. Qin and X. Meng, MPSO-based model of train operation adjustment, *Procedia Engineering*, vol.137, pp.114-123, 2016.

[11] N. J. Radcliffe and P. D. Surry, Formal memetic algorithms, *Lecture Notes in Computer Science*, vol.865, pp.1-16, 1994.

[12] X. Gong, Y. Liu and N. Lohse, Energy and labor aware production scheduling for industrial demand response using adaptive multi-objective memetic algorithm, *IEEE Transactions on Industrial Informatics*, 2018.

[13] Z. Zhang, Y. Sun, H. Xie et al., GMMA: GPU-based multiobjective memetic algorithms for vehicle routing problem with route balancing, *Applied Intelligence*, vol.49, no.1, pp.63-78, 2018.

[14] T. C. Chiang, H. C. Cheng and L. C. Fu, NNMA: An effective memetic algorithm for solving multiobjective permutation flow shop scheduling problems, *Expert Systems with Applications*, vol.38, no.5, pp.5986-5999, 2011.

[15] N. A. AL-Madi, K. A. Maria, E. A. Maria and M. A. AL-Madi, A structured-population human community based genetic algorithm (HCBGA) in a comparison with both the standard genetic algorithm (SGA) and the cellular genetic algorithm (CGA), *ICIC Express Letters*, vol.12, no.12, pp.1267-1275, 2018.

[16] A. A. Ewees, M. A. Elaziz and E. H. Houssein, Improved grasshopper optimization algorithm using opposition-based learning, *Expert Systems with Applications*, vol.112, pp.156-172, 2018.

[17] K. Y. Spencer, P. V. Tsvetkov and J. J. Jarrell, A greedy memetic algorithm for a multi-objective dynamic bin packing problem for storing cooling objects, *Journal of Heuristics*, vol.25, pp.1-45, 2019.