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An Improved Memetic Algorithm for Traction Characteristic Curve Fitting of Urban Rail Vehicle

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Abstract. An Improved Memetic Algorithm (IMA) for the traction characteristic curve fitting of urban rail vehicle is studied in this paper. Combining strong global search ability of Genetic Algorithm (GA), quick convergence ability of Fruit Fly Algorithm (FFA) and strong local search ability of Hill Climbing Algorithm (HCA), this paper constructs a hybrid algorithm to improve the search efficiency for MA. A univariate equation with n orders of the instantaneous speed is adopted for segmented curve fitting because of its simple structure. Besides, this paper proposes a new learning mechanism that enables them to learn from each other between elite individuals and non-elite individuals for MA. Finally, In the Matlab2016a GUI platform, by using several different curve fitting optimization algorithms to carry out simulation experiments, simulation results show that the IMA can find more accurate traction characteristics fitting curve at the same condition.

Keywords: fruit fly algorithm, genetic algorithm, memetic algorithm, reverse learning, traction characteristic curve

1 Introduction

In urban rail transit system, the traction motor is the core part of the vehicle. The traction characteristic curve is one of the most important characteristic curves for the urban rail vehicle, which affects the safety, comfort and economy of the urban rail transit operation [1]. The accuracy of traction characteristic curve fitting has great influence on the traction characteristic analysis, the generation of simulated running track and the simulated conclusion data [2]. Because uncertain factors are numerous and relationships of them are very complex for rail transit vehicles, it is very difficult to obtain the accurate traction characteristic fitting curve only by using the traditional optimization algorithms. The traditional optimization algorithms such as GA, Particle Swarm Optimization (PSO), Firefly Algorithm (FA) and so on, has some disadvantages. It is easy for traditional optimization algorithms to fall into the local optimum, and there are also problems of blind searching, premature stagnation and slow convergence in the iteration. In order to improve the optimization performance of traditional optimization algorithms, many literatures have studied and improved traditional optimization algorithms. For example, in [3], the Hybrid Particle Swarm Optimization algorithm (HPSO) of Simplex Algorithm(SM) and PSO combined was used to obtain the soil water characteristic curve. In [4], an identification method of the wind turbine power characteristic curve based on the GA was proposed. With the piecewise linearization method, the wind turbine power characteristic curve is divided into several sections. In [5], the FA was proposed to solve the nonlinear fitting problem of soil water characteristic curve model parameters. Although the above

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algorithms can solve general optimization problems, there are still some defects such as the slow-convergence and local convergence.

In addition, many new intelligent optimization algorithms can also solve complex optimization problems. In [6], an Improved Fruit Fly Optimization (IFFO) algorithm was presented for solving continuous function optimization problems. Compared with the GA, the significant advantage of IFFO algorithm is that it does not need to give the stable domain of the parameters, but only needs a set of stable parameters. In [7], HCA was used to optimize the correlation-immune function which could get much Boolean functions with high nonlinearity. Compared with other optimization algorithms, the HCA selects some nodes by the heuristic method, so as to greatly improve the optimization efficiency of the algorithm. In [8], a chicken swarm optimization with positive learning and reverse learning was proposed to solve the defect that traditional chicken swarm optimization is easy to fall into local optimum. In [9], the MA based on the tabu search algorithm was introduced to improve the MA based on the HCA to improve the efficiency of the implementation of the entire cloud environment.

In order to improve the accuracy of traction characteristic curve fitting, based on literature [4], literature [6], literature [7], literature [8] and literature [9], the IMA is proposed in this paper. The IMA combines strong global search ability of GA, quick convergence ability of FFA and strong local search ability of HCA, which greatly improves the searching ability of the algorithm. In addition, the learning mechanism of positive learning and reverse learning is added into the MA. As for the IMA, the individual needs to learn from the elite individual, but it will learn reversely from the non-elite individual to jump out of the local optimum when stagnant. Simulation results show that the IMA adopted in this paper has better optimization performance by comparing with other optimization algorithms.

2 Problem Description and Mathematical Model Establishment

The operation process of urban rail vehicle is mainly affected by the traction. In general, the traction characteristic curve of urban rail vehicle is partitioned into three regions for design: constant torque region, constant power region, and power reduction region (natural characteristic region). In the constant torque region, the traction power of the urban rail vehicle is proportional to the speed, and the traction force is maximum and constant. The function is as follows:

$$F(v) = F_{\max}. \tag{1}$$

where $F(v)$ is the instantaneous traction of vehicle; v is the instantaneous speed of vehicle; $F_{\max}$ is the maximum traction of vehicle.

In the constant power region, the traction power of urban rail vehicle is maximum and constant, and the traction force is inversely proportional to the instantaneous speed. The specific formula is given by:

$$F(v) = P_{\max} / v. \tag{2}$$

where $P_{\max}$ is the maximum traction power.

In the power reduction region, the traction force is inversely proportional to the instantaneous speed square, and the specific formula is:

$$F(v) = P_{\max} \times v_d / v^2. \tag{3}$$

where v_d is the switching speed between constant power region and power reduction region. The tractive characteristic design curve is shown in Fig. 1, and v_c is the switching speed between constant torque region and constant power region.

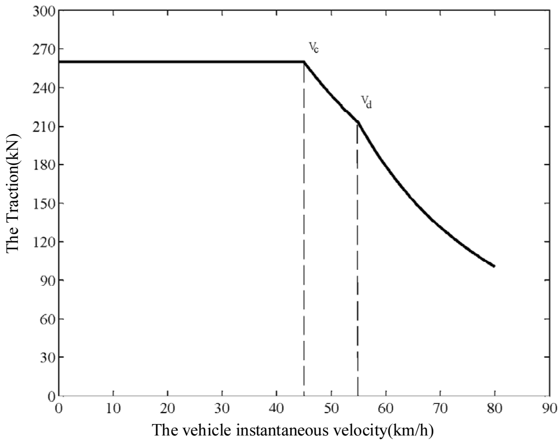

Fig. 1. The tractive characteristic design curve of urban rail transit vehicle

The traction is man-set according to the requirement of urban rail transit, and the actual traction should be equal to the designed value in theory. Due to the aging of traction motor, the dry running line, the wear and tear of wheels and so on, there still exists the difference between the actual traction characteristic curve and the designed curve. The actual traction characteristic curve is shown in Fig. 2.

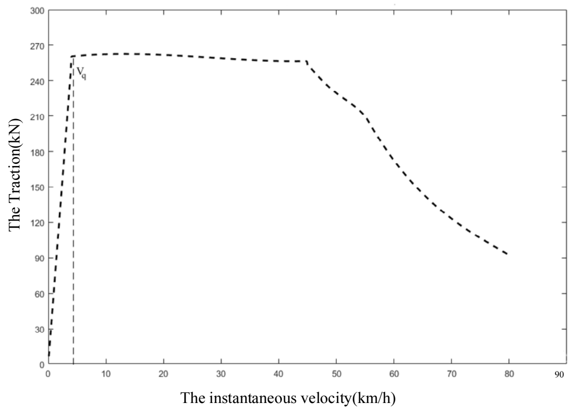

Fig. 2. The actual tractive characteristic curve of urban rail transit vehicles

In Fig. 2, v_q is the switching speed between the tractive starting region and the constant torque region. In reality, the starting process is an almost uniformly accelerated process, which will make passengers more comfortable.

The mathematical model of optimization problem for traction curve fitting of urban rail vehicle is described as follows:

$$\min F_{Verr}\left(v, F_r, F'\right). \tag{4}$$

$$S.T.\begin{cases} F_{Verr} = \sum_{j=1}^{n} \dfrac{\left|F'(j) - F_r(j)\right|}{F'(j)} & \\ j = fit(v) \in [1, n] & \\ F'(v) \approx F_r(v) \approx F(v) = F_{\max} & v_q \le v < v_c \\ F'(v) \approx F_r(v) \approx F(v) = {P_{\max}}/{v} & v_c \le v < v_d \\ F'(v) \approx F_r(v) \approx F(v) = {P_{\max} \times v_d}/{v^2} & v_d \le v \le v_{\max} \end{cases}. \tag{5}$$

where F' represents the actual traction; F_r represents the corresponding value of the traction characteristic fitting curve; F represents the designed traction; j represents the discrete value of the instantaneous velocity v, which is the integer of v; F_{Verr} indicates the cumulative error between traction characteristic fitting curve and actual traction characteristic curve.

According to the above mathematical model, various identification algorithms and optimization algorithms can be used for the curve fitting. In order to obtain more accurate traction characteristic curve, combining with the cumulative running distance of the vehicle from static state to the state of maximum speed on the straight track [10], the above mathematical model is further improved, which is described as:

$$Object\begin{cases} F(v,F_r,F') = (F_{Verr}(v,F_r,F'), \\ \qquad\qquad F_{Serr}(v,F_r,F')) \\ \min\left\{F(v,F_r,F')\right\} \end{cases}. \quad \textbf{(6)}$$

$$S.T.\begin{cases} \dfrac{dt}{ds} = \dfrac{1}{v} \\ mv\dfrac{dv}{ds} = f(v) - w(v) \\ t(0) = v(0) = 0, v(s) < v_{\max} \\ F_{Verr} = \sum_{j=1}^{n} \dfrac{\left|F'(j) - F_r(j)\right|}{F'(j)} \\ F_{Serr} = \dfrac{\left|F_s(F') - F_s(F_r)\right|}{F_s(F')} \\ j = fit(v) \in [1,n] \end{cases}. \quad \textbf{(7)}$$

where s represents the actual running position of the vehicle; t represents the actual running time; $v_{\max}$ represents the maximum running speed; $w(u,s)$ represents the basic resistance of the vehicle on the straight track, which is determined by the instantaneous speed and the position; F_s indicates the cumulative running distance of the vehicle from static state to the state of maximum speed on the straight track; F_{Serr} represents cumulative running distance error between the traction characteristic fitting curve and actual traction characteristic curve.

Obviously, mathematical models described in the equation (6) and (7) are quite realistic, and better results can be obtained in theory. The conventional systematic identification methods such as least square method, gradient correction method and maximum likelihood method are not good at solving this complex model based on operation process. For the model that is not easy to be solved in conventional systematic identification methods, it is easy to obtain more satisfying optimization results by using intelligent algorithms such as GA, Ant Colony Algorithm (ACA), Differential Evolution Algorithm (DEA) and so on. However, these optimization algorithms tend to fall into local convergence at the end of the iteration, which makes the improvement of optimization results less than expected. The MA is the combination based on global search and local heuristic search [11], which makes its search efficiency several orders of magnitude faster than the traditional GA in some areas. So the MA is widely used in relative fields, and it can obtain satisfying results [12].

3 Method of the IMA

3.1 Segmented Fitting Function

Generally, the actual traction characteristic curve is relatively smooth, and tendencies of the traction curve in different characteristic regions are relatively fixed. Based on the above situation, this paper uses a univariate equation with n orders of the instantaneous speed v for segmented curve fitting. On the one hand, this fitting method is easy to obtain tractive characteristic curve close to the actual curve. On the other hand, there is no exponential function, logarithmic function, trigonometric function and other complex functions, so it is easy to find the optimal solution. The specific segmented fitting function is as follows:

$$\begin{cases} F_r(v) = x_n^k \times v^n + ... + x_1^k \times v + x_0^k \quad v \in V^k \\ V^1 = \{0, v_q\}, V^2 = \{v_q, v_c\}, V^3 = \{v_c, v_d\}, V^4 = \{v_d, v_{\max}\} \end{cases} . \tag{8}$$

where V^k represents the characteristic region; x_i^k is the polynomial coefficient of a univariate equation with n orders; v_q, v_c, v_d, x_i^k are decision variables.

3.2 Framework of the MA

Pablo Moscato first proposed MA 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 [13]. In this framework, different search strategies can be used to construct different memetic algorithms. In the paper, the global search strategy uses Genetic Fruit Fly Optimization Algorithm (GFFOA), and the local search strategy uses HCA.

3.2.1 Improvement of Global Search for FFA

FFA is a new global optimization evolutionary algorithm proposed by Wen Chao Pan in 2011 [14]. The parameter structure of FFA is simple and easy to adjust. However, because the FFA makes all individuals close to the optimal individual during the iteration, it is extremely easy for FFA to get stuck in local optimum due to the lack of individual diversity [15]. In order to keep individual diversity, a hybrid algorithm combining GA with FFA is used to globally search. The hybrid algorithm steps are as follows:

Step 1. Randomly initialize the positions X_{axis}, Y_{axis} of fruit fly population.

Step 2. Randomly assign the direction and distance of the fruit fly individual by using the olfactory to search for food.

$$\begin{cases} x_j = X_{axis} + R \times rand() \\ y_j = Y_{ayis} + R \times rand() \end{cases} . \tag{9}$$

Step 3. Since the location of food is not known, the distance D_j between the current position of the fruit fly individual and the origin position is calculated first, and then the judgment value S_j (S_j is the reciprocal of D_j) of taste concentration is calculated.

$$\begin{cases} D_j = \sqrt{x_j^2 + y_j^2} \\ S_j = 1/D_j \end{cases} . \tag{10}$$

Step 4. The judgment value S_j of taste concentration is brought into the fitness function f in order to get the taste concentration $Smell_j$.

$$Smell_j = f\left(S_j\right). \tag{11}$$

where S_j represents the set of decision variables for the segmented fitting function; $Smell_j$ denotes the fitness function value obtained by the formula (6) and (7) when the decision variables are determined.

Step 5. Selection, crossover and mutation operations are performed, and find out the individual of the lowest taste concentration in the genetic fruit fly population.

$$[bestSmell\ bestinde] = \min(smell_j). \tag{12}$$

Step 6. Record and maintain the best taste concentration value *bestSmell* and its corresponding coordinates X_{axis}, Y_{axis}.

$$\begin{cases} Smellbest = bestSmell \\ X_{axis} = X(bestIndex) \\ Y_{axis} = Y(bestIndex) \end{cases} . \quad \textbf{(13)}$$

where X_{axis} and Y_{axis} is the fruit fly position of the next iteration [16].

3.2.2 Improvement of Local Searching for HCA.

HCA is a greedy algorithm that is often used in local search. Firstly, select an optimal solution of the current problem as the hill climbing position. Secondly, appropriately change the optimal solution in its proper neighborhood to seek a better solution. If the better solution is found, then the original solution is replaced by the better new solution [7]. This paper gives the following strategy.

The optimal fruit fly individual in each iteration obtained by GFFOA is selected as the hill climbing position. Partial parameters in the decision variables v_q, v_c, v_d, x_i^k are remained, the other parameters that are not retained in the decision variables v_q, v_c, v_d, x_i^k are replaced by a slightly different value. According to the above mathematical model described in formula (6) and (7), the fitness function value of the new solution is calculated. If the fitness function value of the new solution is better than the current optimization solution, the latter is replaced by the former. The specific flowchart is shown in Fig. 3.

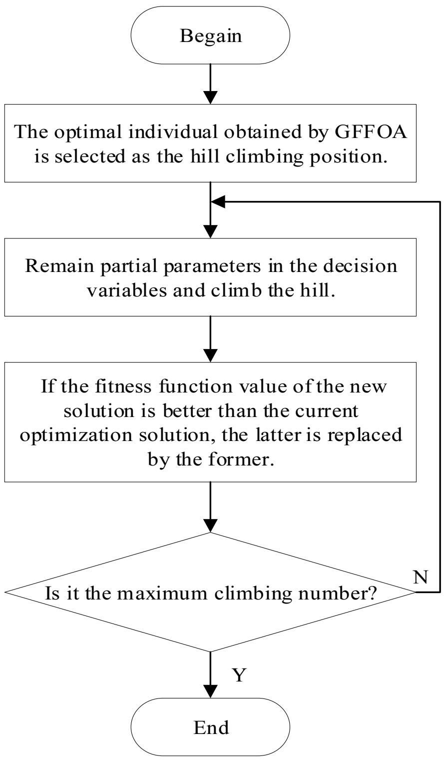

Fig. 3. The flowchart of HCA

3.3 Improvement of the Learning Mechanism for MA

The MA is an optimization algorithm based on emulated cultural evolution [17]. There exists certain limitation of the evolutionary environment in the long evolutionary process. After a long time, the elite population will gradually evolve to a state of the comparative advantage for certain features, which governs the population in some extent. It is difficult for the population to continue to evolve in this state mentioned above, which is also known as equilibrium state. At this time, generally at the end of the iterative convergence for MA, it is extremely difficult for non-elite individuals to enter the elite population and the elite is also hard to evolve further, which makes it difficult for MA to converge globally. Therefore, the MA based on the core idea of competition has great defects in the evolutionary system. Considering the optimization problem of tractive curve fitting for urban rail transit vehicle, in order to improve the fitting precision, this paper proposes a new learning mechanism that enables them to learn from each other between elite individuals and non-elite individuals for MA. The specific schematic diagram is shown in Fig. 4.

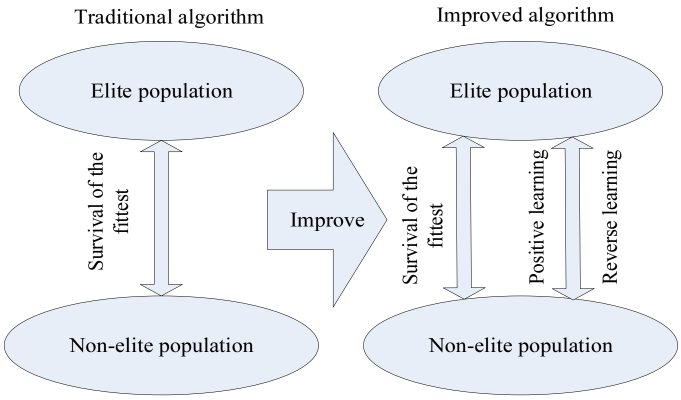

Fig. 4. The learning mechanism of positive learning and reverse learning

For an individual, two optimization indexes of the cumulative traction error and the cumulative running distance error are investigated. It is impossible for an individual in the non-elite population to have two indexes that are better than the individual in the elite population. But it is very possible for a non-elite individual to have an index which is better than the elite individual. At this time, it is necessary for the elite individual to learn from the advantage of the non-elite individual, which is the reverse learning. For a non-elite individual, if both indexes of it are inferior to another elite individual, the former needs to learn from the latter, which is the positive learning [8]. This paper formulates the following learning strategy:

Positive learning. The partial parameters for the individual who needs positive learning are replaced by those of the elite individual who is learned, and the number of parameters depends on the positive learning rate P_p. Other parameters which are not replaced are replaced by a slightly different value. By means of positive learning, the blind searching of individuals in the whole solution space is avoided and the iterative convergence time of the algorithm is reduced.

Reverse learning. Although the above positive learning can make the algorithm enter more efficient region, the algorithm is still easy to fall into the local optimum and hard to jump out of that. In the MA, individuals should have both the ability of positive learning and the ability of reverse learning. The partial parameters for the individual who needs reverse learning are replaced by those of the non-elite individual who is learned, and the number of parameters depends on the reverse learning rate P_r. Other parameters which are not replaced are replaced by a slightly different value.

4 Simulation Experiment

4.1 Initialization of the Data

This paper uses the data of the unbar rail vehicle for Jinpu line in Dalian, and the corresponding characteristic curves are shown in Fig. 5.

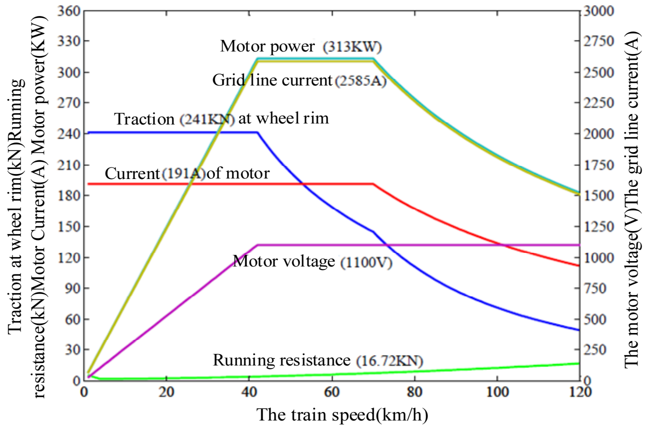

Fig. 5. The characteristics curves of urban rail vehicle for Jinpu line

In Fig. 5, the traction characteristic curve is the most basic and the most important curve, which is because all other curves except the running resistance are based on the traction characteristic curve. The actual traction characteristic curve of urban rail vehicle is slightly different from the design curve, so there is also some difference in the calculation of the vehicle operation. This paper collects the relative running data of urban rail vehicle for Jinpu line on the straight track under the AW3 load from static state to the state of the highest speed, such as the actual traction force and the actual running distance. The specific tractive characteristic curve and tractive running distance curve on the straight track are described in Fig. 6.

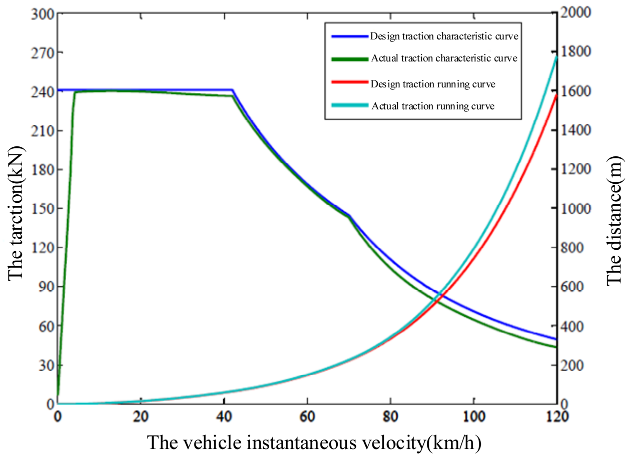

Fig. 6. The tractive characteristic curve and tractive running distance curve on the straight track

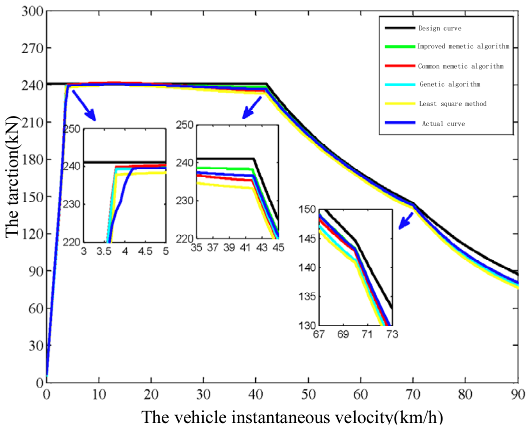

Fig. 7. The traction characteristics fitting curves for various algorithms

4.2 Simulation Results

The program is based on Matlab2016a in the paper. This paper uses LSM, GA, Common Memetic Algorithm (CMA) and IMA to obtain the tractive characteristic fitting curve and related results under the above testing data. The global search of CMA adopts GA, and the local search adopts Simulated Annealing Algorithm (SAA). The parameters of GA are set as follows: the number of individuals is 20, the crossover and mutation probability are 30%, and the iteration number is 300. The parameters of the CMA are set as follows: the initial temperature is 400, the dropping coefficient of temperature is 0.8, the temperature of termination is 0.1, the number of individuals is 20, the crossover and mutation probability are 30%, and the iteration number is 300. The parameters of the IMA are set as follows: the number of HCA is 10, the number of fruit fly individuals is 20, the crossover and mutation probability are 30%, the number of iterations is 300, the positive learning rate is 30%, and the reverse learning rate is 20%. The tractive characteristic fitting curves obtained by the above algorithms are shown in Fig. 7 and the running distance curves obtained by the above algorithms on the straight track are shown in Fig. 8.

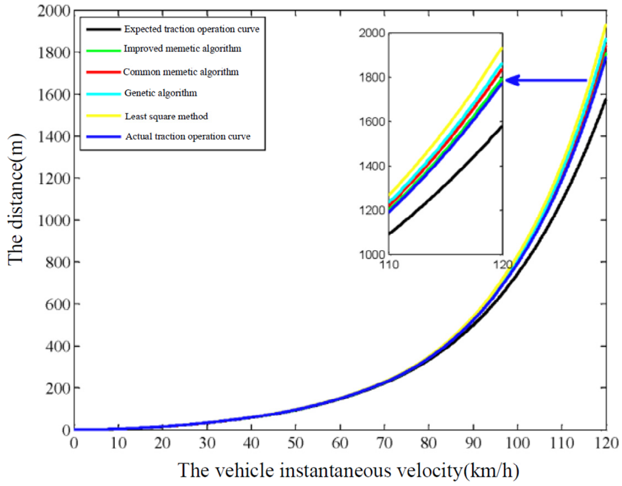

Fig. 8. The running distance curves obtained by the above algorithms on the straight track

The parameter x_i^k of a univariate equation with n orders for the tractive segmented fitting curve is obtained by the above algorithms, and the specific parameters are shown in Table 1. The switching speed of the traction fitting curve is obtained by the above algorithms, as shown in Table 2.

Table 1. The polynomial coefficients of traction segmented fitting functions obtained by various algorithms

Optimization algorithm	$V^1=\{0,v_q\}$	$V^2=\{v_q,v_c\}$	$V^3=\{v_c,v_d\}$	$V^4=\{v_d,v_{\max}\}$
LSM	1.9535 -12.9095 27.2902 36.1086 3.5792	0.00038 -0.0333 0.6707 235.7257	0.000127 -0.0293 2.5568 -103.1143 1828.827	2.1×10-5 -0.00872 1.3683 -97.6206 2755.0372
GA	0.69095 -2.2362 -0.162 58.9961 -1.2259	0.000227 -0.01999 0.4024 238.03545	7.18×10^{-5} -0.0171 1.5681 -68.211 1378.917	1.88×10^{-5} -0.007829 1.2354 -88.8565 2541.386
CMA	0.7903 -2.8087 0.8748 58.1246 -1.132	0.00038 -0.03331 0.6707 237.72575	0.00013 -0.02995 2.6091 -104.976 1855.0905	1.99×10^{-5} -0.00828 1.303 -93.319 2651.8632
IMA	1.2694 -7.4842 13.8737 48.0405 1.3226	0.000114 -0.009994 0.20121 239.01772	8.09×10^{-5} -0.01906 1.7199 -73.3274 1443.255	1.9×10^{-5} -0.00784 1.2377 -89.0174 2547.389

Table 2. The switching speed of the traction fitting curve obtained by various algorithms (km/h)

Optimization algorithm	v_q	v_c	v_d
LSM	3.851	41.875	70.411
GA	3.864	41.829	70.315
CMA	3.877	41.703	70.241
IMA	3.882	41.616	70.209

It can be seen from Table 1, the segmented functions of all the intervals are a univariate equation with 4 orders, except that the function in the interval $V^2 = \{v_q, v_c\}$ is a univariate equation with 3 orders. In the table, the polynomial coefficients obtained by various algorithms in the corresponding interval are given in order. For example, the fitting function for the interval $V^1 = \{0, v_q\}$ of the LSM is $F_r(v) = 1.9535v^4 - 12.9095v^3 + 27.2902v^2 + 36.1086v + 3.5792$. When the instantaneous velocity is 3.85km/h, the traction force obtained by the above formula is 233.824kN. The traction of the key point for the instantaneous velocity is obtained, as shown in Table 3. The running distance of the key point for the instantaneous velocity is obtained, as shown in Table 4.

Table 3. The traction of the key points for the instantaneous velocity obtained by various algorithms (kN)

Optimization algorithm	3.8km/h	41.5km/h	70km/h	120km/h
Actual curve	228.12	236.551	142.966	43.2311
LSM	237.824	233.252	140.713	39.2493
GA	239.288	236.547	141.317	40.8824
CMA	239.814	235.251	142.585	41.6155
IMA	239.644	238.276	143.157	42.6817

Table 4. The running distance of instantaneous velocity key points obtained by various algorithms (m)

Optimization algorithm	3.8km/h	41.5km/h	70km/h	120km/h
Actual curve	1.134	63.509	225.364	1770.229
LSM	1.150	64.069	228.653	1928.835
GA	1.158	63.526	227.242	1859.015
CMA	1.162	63.546	226.132	1831.200
IMA	1.135	63.293	224.970	1790.398

It can be seen from Table 3 and Table 4, compared with other algorithms, the traction of key points for the instantaneous velocity obtained by the IMA is obviously closest to the actual traction, and the running distance of key points for the instantaneous velocity is also closest to the actual running distance. Therefore, the IMA has better search performance. The cumulative traction error and the cumulative running distance error between the curves obtained by various algorithms and the actual curve are obtained, as shown in Table 5.

Table 5. The accumulative traction error (kN) and the accumulative running distance error (m) between the results obtained by various algorithms and the actual results

Optimization algorithm	Accumulative traction error	Accumulative running error
LSM	1.2451	158.5752
GA	1.2373	88.7551
CMA	1.2140	60.9402
IMA	0.5030	20.1388

According to above simulation figures and conclusion data, the curve obtained by the IMA has better fitting effect, which is almost coincided with the actual curve. Compared with CMA, the error between results obtain by IMA and the actual results greatly decreases. Compared with other algorithms, the error improvement of IMA is also greater. When the cumulative traction error and the cumulative running distance error are both less than a certain threshold value, the difference between the calculation results and the actual results can be neglected. The threshold value is 1kN and 50m respectively in the paper. It can be seen from Table 5 that the optimization effect of the IMA in this paper is extremely good, which can apparently meet the expectations.

5 Conclusion

The mathematical model of tractive characteristic curve fitting for the urban rail vehicle is built based on the traction characteristics and the actual testing data, and the IMA is proposed in this paper. The global search of the IMA adopts GFFOA, and the local search adopts HCA. The univariate equation with n orders of the instantaneous speed is adopted for segmented curve fitting in the paper because of its simple structure. This paper proposes a new learning mechanism that enables them to learn from each other between elite individuals and non-elite individuals for MA. This paper collects the relative running data of urban rail vehicles for Jinpu line in Dalian as the simulation experimental data. By comparing simulation results obtained by various algorithms, the fitting curve of the IMA is closest to the actual curve, which can greatly improve inaccurate defects of calculation results.

In fact, if the complex functions such as logarithm or exponential function are introduced into the curve fitting function and the complex framework of MA is adopted, the accuracy of the algorithm can be greatly improved. However, for the practical engineering application problem like this, it is not advisable to obtain only very small improvements through huge computational cost. Therefore, the further improvement should be considered for computing efficiency of the algorithm.

Acknowledgements

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