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Energy-Efficient Operation Curve Optimization for High-Speed Train Based on GSO Algorithm

Wei Li[1], Sizhe Zhao[1], Kang Li[1,2], Yi Xing[1,3], Gaofeng Liu[1], Jilong Liu [1,4]

[1] Cent South Univ, Sch Traff & Transportat Engn, Changsha, China

[2] Univ Leeds, Sch Elect & Elect Engn, Leeds, W Yorkshire, England

[3] CRSC Research & Design Institute Group Co., Ltd. Beijing, China

[4]CRRC QINGDAO SIFANG Co., Ltd. Shandong, China

Abstract: The demand for high-speed automatic train operation (ATO) system brings new opportunities and challenges for the high-speed railway field, among which the requirements of energy consumption, punctuality, safety and smoothness are increasing, especially the research on energy saving of high-speed trains ushers in a broader development space. This paper combines the characteristics of high-speed train ATO system, constructs the quantitative functions of four energy-saving performance indexes, establishes the multi-objective optimization model of train operation curve, and proposes the energy-saving optimization method of train operation curve based on Glowworm Swarm Optimization (GSO) algorithm. The simulation results show that the train operation curve generated by the high-speed train operation curve optimization method based on the GSO algorithm can save about 16.9% of electrical energy consumption per kilometer compared with the operation curve generated by other optimization algorithms, which verifies the effectiveness of the method and provides theoretical support for practical application.

Keywords: Energy-efficient operation; Multi-objective optimization; GSO algorithm; High-speed train; Train operation curve

1 Introduction

The development of high-speed trains has made the research on energy-saving operation more and more urgent and demanding. Among them, operation mode optimization of the train is one of the easiest and feasible ways to achieve energy consumption reduction in high-speed train operation, based on which a large number of experimental studies have been conducted by domestic and foreign scholars.

The continuous development of computer network technology and intelligent control theory has provided new ideas and in-depth development for the research of train energy saving, and many scholars have carried out the optimization solution of this problem by using genetic algorithm, neural network, simulated annealing, ant colony algorithm, etc. T Xie [1] searched for the train inactivity point under the constraints of speed limit and time limit and carried out the solution of the problem by simulated annealing method. Y Bai [2] studied the real-time optimization problem of train operation based on previous research and developed a fuzzy predictive control method to reduce the energy consumption of train operation by providing locomotive operation commands according to the speed limit. L Zhou *et al.* [3] searched the speed/acceleration curve using dynamic programming algorithm and developed a modeling framework for macro and micro computation of train operation diagrams, and the corresponding theoretical study was tested practically on the Beijing-Shanghai line. Scholars Shuqi Liu

[4] conducted a related study based on the ATO control strategy, and based on this, they proposed a single-vehicle energy-saving optimization model to optimize the recommended operating curve and ATO system tracking control measurements. Zhang Miao *et al.* [5] designed a train operation energy consumption optimization model based on the Q-learning algorithm. Tang Tao *et al.* [6] used an ant colony algorithm to optimize the train ATO control strategy, which ultimately reduced the energy consumption of single-train operation by 5.67%.

The existing studies can be grouped into two categories, direct and indirect methods, according to the optimization methods used. Both the direct method represented by dynamic programming and the indirect method represented by the extreme value principle and intelligent algorithm can solve the operation curve optimization problem, but most of them have problems such as complicated modeling, influenced by parameters, slow solving process and easy to fall into the optimal solution, while the group intelligent algorithm can adapt well to the complex and nonlinear train operation process, and the use of intelligent algorithm to solve the train operation curve has become the development trend of the research of the train energy-saving optimization problem. In this paper, based on the research of other scholars, we introduce the GSO algorithm, a population intelligence algorithm, to solve the energy-saving train operation optimization problem, and verify the effectiveness of the method through simulation.

2 Analysis of Energy-saving Operation and Its Control Impact Based on ATO

The architecture of the onboard ATO system for high-speed trains can be divided into two main layers, as shown in **Fig. 1**. The upper layer is the optimization layer, which is mainly responsible for generating the reference operation curve under the given constraints; the lower layer is the control layer, which is responsible for comparing the current speed of the train with the target speed in the reference operation curve and outputting control commands to realize the traction operation of the train.

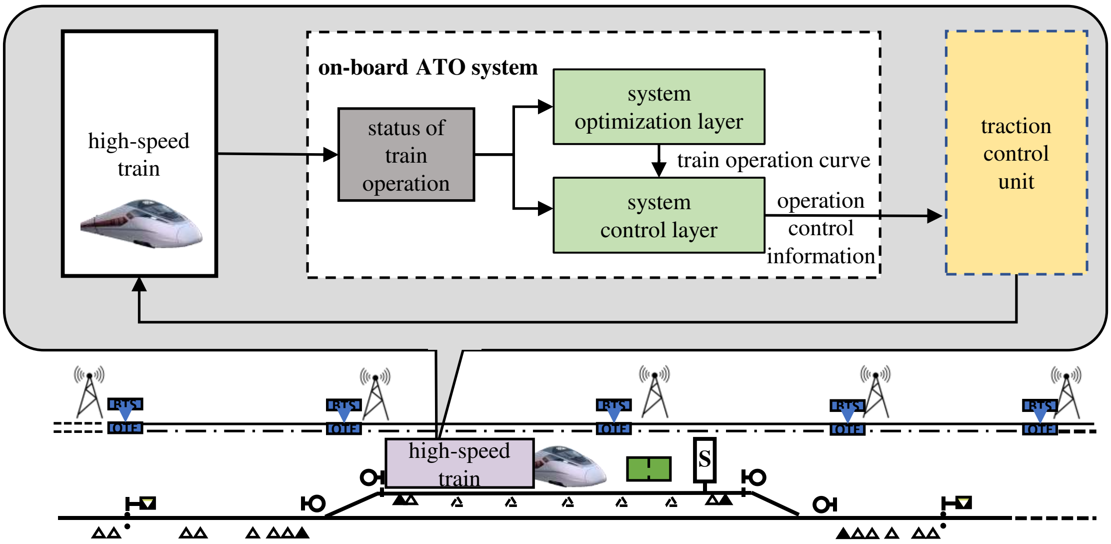

Fig. 1. Schematic structure of onboard ATO system for high-speed trains.

In the actual operation of high-speed trains, the operation status is changed according to the control of the train operation curve, so optimizing the operation curve of high-speed trains can achieve the purpose of saving energy for high-speed trains. To carry out energy-saving train operation optimization, we need to analyze and model the train operation process first.

2.1 Analysis of High-speed Train Operation Process

Table 1. Symbols.

Symbol	Description
$v(s)$	Speed of the train at position s (m/s)
F_f、F_b	Traction force and braking force on the train (N)
F_r、F_g、F_c	Basic resistance, additional resistance on ramps and additional resistance on curves to the train (N)
M	Mass of the train (t)
a, b, c	Davis index based on the structure of the train
q	The thousandth of slope
A	Experience coefficient about the resistance of the curve
R	Radius of curve (m)

The train in the process of operation by the locomotive traction and a variety of resistance, which plays an impact on the train traction energy consumption of the force is mainly the train traction, train braking force and train running resistance of the three longitudinal train force, the train in the driving process of the kinetic equation as shown in Equation (1).

$$\frac{dv(s)}{ds} = \frac{F_f - F_b - F_r - F_g - F_c}{v(s) \cdot M \cdot (1+\rho)}$$
$$\begin{cases} F_r = a + b \cdot v + c \cdot v^2 \\ F_g = \pm M \cdot g \cdot q \\ F_c = M \cdot A/R \end{cases} \quad \textbf{(1)}$$

According to the magnitude and direction of the combined force on the train, the train operation condition is composed of six driving conditions: constant-torque traction mode, constant-power traction mode, cruising mode, costing mode, braking mode, and stopping mode. **Fig. 2** shows an ideal train running speed curve, where S_0、S_1、S_2、S_3、S_4、S_5 and S_6 are the coordinates of the distance corresponding to the changeover points of the train running curve conditions.

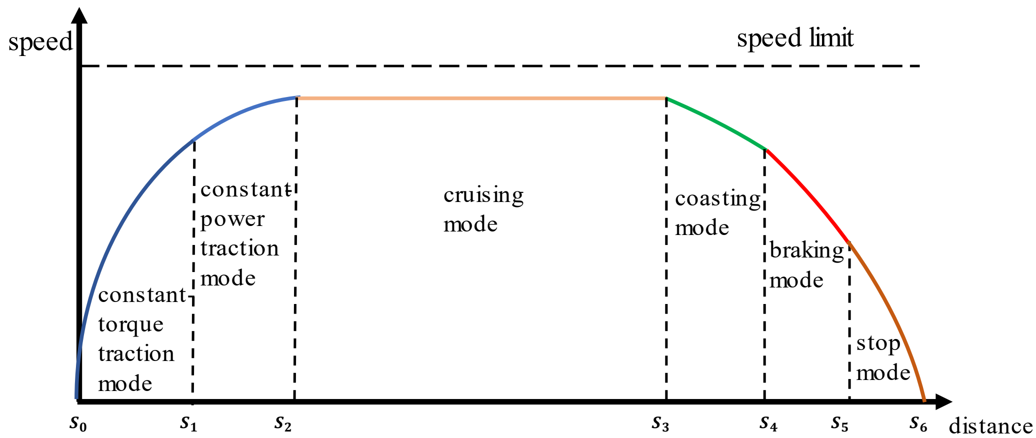

Fig. 2. The running process of the train.

In the train running process corresponding to the curve, the train first accelerates from the starting point S_0 to the next station with constant-torque traction mode, and then switches to constant-power traction mode after reaching a certain driving speed. When the train runs to the S_2 position, the train changes the working condition and drive to the S_3 position in the cruising condition, then the train runs in the coasting condition in the $[S_3, S_4]$ interval, and then change the working condition to the braking condition after driving to the S_4 position by its own inertia, and finally complete the operation in the $[S_5, S_6]$ interval in the stopping condition.

In the actual operation process, the adjustment and change of train operation curve usually do not exceed the six working conditions of constant-power traction mode, constant-torque traction mode, cruising mode, coasting mode, braking mode, and stopping mode. It can be seen that the process of train operation actually relies on the control of the train operation curve to complete the conversion between the various operating conditions. The process between the initial position of the train and the target position can be described by the working condition control sequence and the corresponding working condition running distance so that a set of train maneuvering strategies can be determined. The object of operation curve optimization is the sequence of working conditions and the corresponding sequence of working condition changeover points during the train operation.

2.2 Analysis of High-speed Train Operation Manipulation Strategy

Theoretically, an infinite number of operating curves satisfying a given train operating time limit can be generated according to line conditions, speed limits, etc. Different operating curves correspond to different train maneuvering sequences, and different sets of maneuvering sequences have different performances in terms of energy consumption, passenger comfort, and safety. Under the same conditions of line speed, gradient, and other related factors, the energy consumption of train operation corresponding to different train maneuvering strategies varies up to 30% [7].

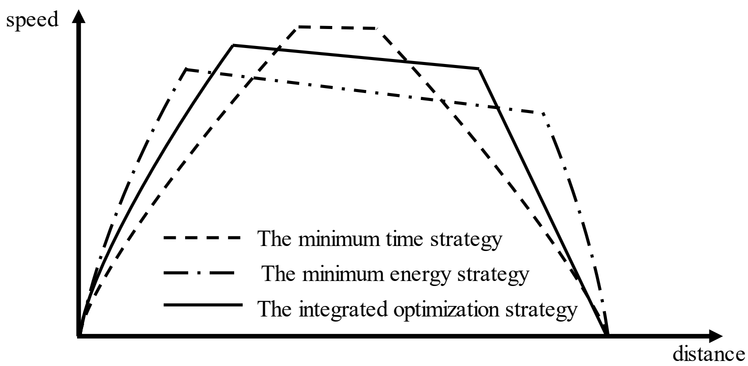

Fig. 3. Three typical driving strategies.

According to the operational needs of the driving strategy classification, common train maneuvering strategy are the minimum time strategy, the minimum energy strategy, and the integrated optimization strategy, three different strategies corresponding to the operating curve schematic as shown in **Fig. 3**. Among them, the minimum time strategy takes time as the most important index of the train operation process to ensure that passengers finish displacement in a short time, and this strategy highlights the importance of punctuality of the train, but running with the maximum driving capacity greatly increases the requirements for the train's performance, and also brings a lot of energy consumption. The driving speed of the minimum energy strategy is lower compared with the driving speed of the shortest time strategy, but it does not take into account factors such as the smoothness of train operation and the accuracy of the stopping position.

In response to the shortcomings of the above two driving strategies, the integrated optimization strategy considers several indicators such as time consumption, energy consumption, and smoothness to save train energy while ensuring punctuality and smooth train operation. The integrated optimization strategy takes into account many performance indicators of train operation, and is a more complex but more realistic real-time variable parameter strategy.

3 Energy-efficient Operation System Method and Basic Control Strategy

The goal of train running curve optimization is to generate a train running speed curve that meets the energy-saving target. The train is affected by factors such as the operating line, signal control, train characteristics, and train smoothness requirements when traveling on the line, so it is necessary to first calculate the train operating curve optimization index and derive the corresponding energy consumption optimization model when researching the curve optimization problem.

Table 2. Symbols.

Symbol	Description
E	Operation energy consumption (kWh)
μ_f	Electrical energy conversion efficiency in motoring mode
s_0	The end of the interval of motoring mode (km)
μ_b	Electrical energy conversion efficiency in braking mode
A	Auxiliary energy efficiency (kWh/h)
ΔT	Deviation value of actual driving time from planned time (s)
ΔS	Deviation value of actual driving distance from planned distance (m)
T, S	Actual running time/distance of the train (s)/(m)
T_0, S_0	Planned running time/distance of the train (s)/(m)
P_t, P_s	Travel time and stopping position index penalty function
τ	Maximum acceptable travel time index, taken as 120s
σ	Maximum acceptable stopping position index, taken as 0.3m
A_{pt}, A_{ps}	A positive integer greater than or equal to 1, taken as 1000
G	Train smoothness index value (maximum value is 1)
$\bar{a}$	The average acceleration in a certain time interval (m/s^2)
Δt	Time interval (s)
f_e	Objective function of the optimization model
$f(v)$	Unit traction of the train (N/kN)
$w(s)$	Unit resistance of the train (N/kN)
$b(v)$	Unit braking force on the train (N/kN)
v_{max}	Speed limitation of the line (km/h)
s_i	Distance traveled in time steps (s)

3.1 Performance Indicators for Operating Curve Optimization

Even if the same train is running on the same line, the energy consumption and time consumption generated by driving with different working sequences are different. Through the analysis of the train operation process, the relevant indicators affecting the train operation can be summarized as energy consumption indicators, travel time and stopping position indicators, and smoothness indicators, and these indicators are used to make a comprehensive evaluation of the train operation process.

Energy consumption index calculation method. The energy consumed by high-speed train operation is composed of traction energy consumption and non-traction energy consumption. Traction energy consumption is expressed as the integral of the tractive force output of the train against the distance under each working condition, and the non-traction train energy consumption is calculated in terms of time. The energy consumption E during the train operation is calculated by the following formula.

$$E = \frac{1}{\mu_f}\int_0^{s_0} F(v)ds + A \times \frac{T}{3600} \tag{2}$$

Travel time and stopping position index calculation method. In actual life, the train runs on the line according to the fixed running plan, and the interval running time and station stopping position are pre-set fixed values. In the process of optimizing the train running curve, the running time error and stopping position error of the train is critical, and when the error value exceeds the set range, the additional penalty value should avoid unnecessary safety hazards caused by the time error or stopping position error being too large.

$$\Delta T = |T - T_0| \tag{3}$$

$$P_t = \begin{cases} 1, & \Delta T \le \tau \\ A_{pt}, & \Delta T > \tau \end{cases} \tag{4}$$

$$\Delta S = |S - S_0| \tag{5}$$

$$P_s = \begin{cases} 1, & \Delta S \le \sigma \\ A_{ps}, & \Delta S > \sigma \end{cases} \tag{6}$$

Smoothness index calculation method. The intense speed changes during the train operation will react with the inertia of the passengers and bring uncomfortable riding experience for them. In this paper, the smoothness of the train driving is taken into consideration as one of the performance indicators, and the average acceleration G value of the high-speed train is calculated as follows.

$$G = \frac{\bar{a}}{\Delta t} \tag{7}$$

According to the train dynamics theory introduced in this section and the indicators of energy consumption of train operation, the mathematical model of high-speed train operation curve optimization is established as follows.

$$\begin{gathered} \min J = k_1 \textstyle\sum_{i=1}^{n} E_k + k_2 |T_0 - \sum_{i=1}^{n} T_k| + k_3 |S_0 - \sum_{i=1}^{n} S_k| + k_4 max\{G\} \\ s.t. \begin{cases} v = ds/dt, \\ m \cdot dv/dt = f(v) - w(s) - b(v), \\ 0 \le s_i \le S, i = 1,2,\cdots,n \;\; s_1 = 0, s_n = S, \\ v(0) = v(S) = 0, v(s_i) \le v_{max} \\ t(0) = 0, t(S) = T_0, 0 \le t(s_i) \le T_0. \end{cases} \end{gathered} \tag{8}$$

3.2 Analysis of Train Operation Curve Optimization Process

The train operation optimization process analysis is the basis for combining the train operation optimization problem with the optimization algorithm, which facilitates the following transformation of the train operation maneuvering strategy using the algorithm rules. The train operation curve optimization problem can be translated into solving the optimal maneuvering scheme from the departure point s_0 to the destination s_n under the constraints of punctuality, energy saving, smoothness, etc. The evaluation of the advantages and disadvantages is determined by the performance index model, and the content of the scheme specifically includes the sequence of working condition transition points $S = [s_1, s_2 \cdots, s_{n-1}]$ and the sequence of working conditions $U = [u_1, u_2, \cdots, u_n]$, in the solution process, the focus needs to be on the selection of the interval and the selection of operating conditions, the conversion points, and their corresponding conditions are shown in **Fig. 4**.

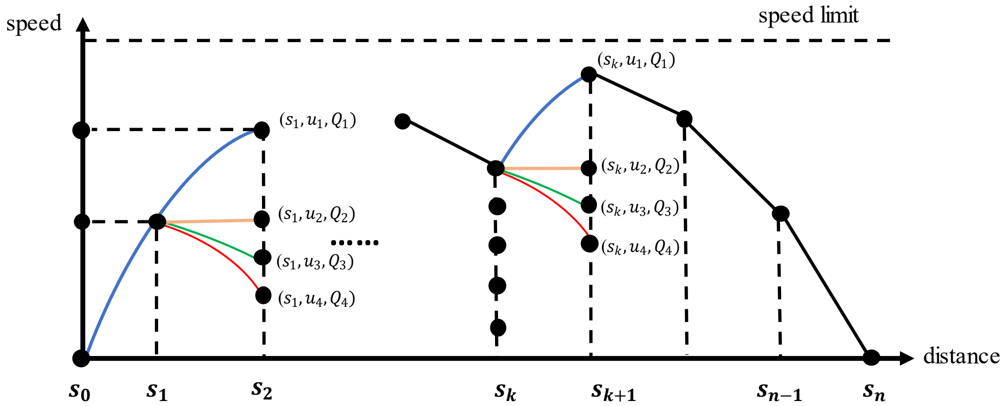

Fig. 4. Schematic diagram of the basic policy

As shown in **Fig. 4**, the selection of working conditions at each working condition changeover point has an impact on the operation status of the next stage and the overall operational performance. The state of the train at working condition changeover point s_2 is determined by the working condition taken at working condition changeover point s_1 and the duration of this working condition. If the train takes working condition u_1 at working condition changeover point s_1 and continues to travel, then the expected benefit achieved when the train travels to working condition changeover point s_2 is Q_1, which is calculated according to Equation (8), the lower the expected benefit the better the optimization effect.

According to the principles of energy-saving train operation [8, 9, 10], the train adopts the maximum tractive force in the starting phase $[S_0, S_1]$ and the maximum braking force in the braking phase $[S_{n-1}, S_n]$ to achieve the effect of energy-saving and consumption reduction, and adding the idling condition before the stopping and braking phase can effectively increase the passenger's riding comfort. When the train is in the intermediate operation stage, the following strategies can effectively improve the performance indexes to obtain the desired benefits of the optimization function.

(1) Operation at constant acceleration on short-distance level tracks.

(2) Switching to cruising mode on long-distance level tracks if the train reaches the upper operating speed limit ahead of schedule.

(3) On uphill grades, applying partial traction to the train to maintain a state of uniform motion in preparation for downhill coasting.

(4) On the downhill slope, taking full advantage of the slope of the ramp and adopts the coasting mode to achieve the purpose of energy-saving maneuvering, and if the distance of the ramp is long, it

needs to switch to the cruising mode in the middle to run to the end of the ramp.

(5) On undulating ramps, by alternately adopting three working conditions of traction, cruising and coasting, the train makes full use of the conversion of gravitational potential energy and dynamic potential energy, and avoids train braking as much as possible to achieve the effect of energy-saving and smooth operation.

4 Solution Methodology Based on GSO Algorithm

The algorithm used to obtain the global desired benefit of the optimization function has an important impact on the optimization effect of the problem. At present, traditional optimization algorithms such as genetic algorithm encounter bottlenecks in the optimization of train operation. Genetic algorithm uses chromosomes for the binary number representation of the location of the working condition changeover point, and need to determine the working condition beforehand and then proceed to the subsequent steps, so the scale of the solution problem and the actual demand of the working condition will have a certain impact on the results. The GSO algorithm, as a new population intelligence algorithm, has the characteristics of fewer parameters and not easy to fall into the optimal solution [11], the firefly individuals rely on mutual attraction to move, each individual in the population is a candidate solution, the individual firefly with a larger fitness value has a greater attraction, and eventually all fireflies will be concentrated near the firefly with a larger fitness value. The GSO algorithm is simple and easy to understand, uses fewer parameters, has strong search performance, and can better construct and find the optimal solution according to the train operation optimization problem.

The combination of the train operation optimization problem and the optimization algorithm is actually a real-time adjustment of the train operation control strategy scheme through the algorithm rules, directly a strategy as the individual solution to be searched for by the algorithm, and the construction of the fitness evaluation function according to the operation performance index to be targeted, the space searched by the algorithm is based on the corresponding operation plan, operating conditions and other constraints specified range, in this space, each solution corresponds to the corresponding value of the fitness evaluation function, and the algorithm eventually converges to an optimal solution or optimal set of solutions by updating the iterative rules, and the resulting solution of the operating scheme can make the train operation meet the corresponding requirements.

In the process of using GSO algorithm for train operation curve optimization, it is necessary to link each element of the train optimization problem with the key elements in the basic principle of GSO algorithm one by one, and each individual firefly represents a feasible train operation strategy, and each strategy consists of working condition sequence and working condition conversion point.

Setting of algorithm parameter. When using the GSO algorithm to optimize the problem, we should first determine the relevant parameters, including objective values such as fluorophore volatilization coefficients that can be directly referred to and the initial population-related parameters that play a key role in the optimization of the algorithm. If the size of the initial population is too large, the iterative process of the algorithm will be more complicated and the efficiency of the algorithm will be greatly reduced, while if the size of the initial population is set too small, the individuals in the initial solution may not include the better solution, and the optimization effect obtained by repeated iterations will not be satisfactory and the algorithm will easily fall into the local optimum. After multiple comparisons and considerations [12, 13, 14], the basic parameters of the GSO optimization algorithm in the train running curve optimization problem are set as follows.

Table 3. Basic parameters of the GSO optimization algorithm.

Parameter	Description	Parameter Value
ρ	Fluorescein volatility coefficient	0.40
γ	Fluorescein growth coefficient	0.60
B	Perceptual radius coefficient of variation	0.08
n_i	Number of outstanding individuals in the perceptual range	5
l_0	Initial fluorescein value	5
N	Population size	30

Determination of fitness value. Individual fireflies rely on brightness to attract others to achieve position shifting in order to search for the optimal solution, and the brightness of individuals is related to the degree of adaptation. Since the principle of GSO algorithm is that fireflies with greater adaptability have stronger attraction, and smaller performance index parameters have greater superiority in the train operation curve optimization problem, the inverse of the objective function value is taken. k is the corresponding weight coefficient of each index, which can be adjusted according to the actual demand.

$$Q = \frac{1}{k_1 \sum_{i=1}^{n} E_k + k_2 \left| T_0 - \sum_{i=1}^{n} T_k \right| + k_3 \left| S_0 - \sum_{i=1}^{n} S_k \right| + k_4 max\{G\}} \tag{9}$$

Update of manipulation sequence. Each individual firefly represents a manipulation scheme, which consists of a sequence of conditions and the location of the transition point, i.e., $x_i = \{U, S\}$, where U denotes the sequence of conditions in the manipulation sequence and S denotes the specific location of the transition point of conditions. When attraction is generated between fireflies for position transfer, individual fireflies need to consider whether to update the work condition sequence, i.e., $x_i(n+1) = \{U_i\,(n), S_i\,(n+1)\}$ or $\{U_j(n), S_i(n+1)\}$, and the selection is based on the adaptation values corresponding to the two solutions.

In summary, the steps of the GSO algorithm for solving the single train interval operation curve optimization are shown in **Fig. 5**.

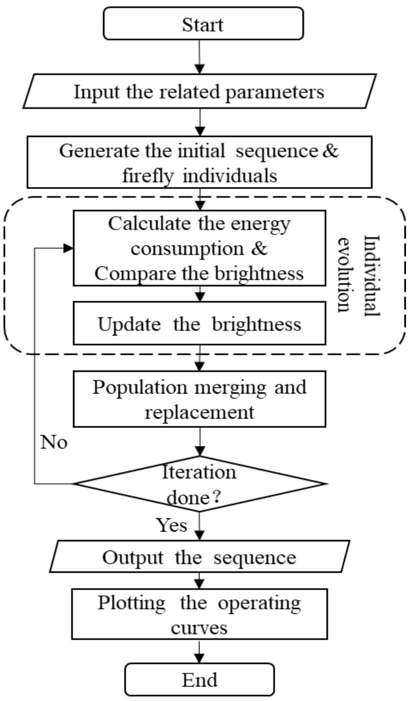

Fig. 5. Flowchart of Solution methodology based on GSO algorithm.

5 Simulation and Verification

The simulation train adopts CR400BF type locomotive with 4 moving and 4 dragging groups, and the train mass is 913t, and the simulation data refers to the actual line data with the length of 58km between Heishan North Station and Fuxin Station of Beijing-Shenzhen Passenger Dedicated Line. The train model and algorithm proposed in this paper are simulated and experimented under the conditions of specific train properties and line parameters. The train parameters and line parameters involved in the algorithm are the same as those in the literature [5], and the specific data are shown in **Table 4**.

Combine the GSO algorithm with the line situation, we can set the population number to 30, the maximum number of iterations to 200, the energy consumption performance index coefficient k_1=0.35, the time performance index coefficient k_2= 0.35, the stopping position performance index coefficient k_3= 0.20, and the smoothness performance index coefficient k_4= 0.10.

Table 4. Line parameters and train-related parameters.

Parameter	Description	Parameter Value
S_0	Length of the line	58km
T_0	Planned running time of the train	23min
v_{max}	Speed limit for the whole road	288km/h
$w_0(v)$	Basic resistance of the train	$0.399 + 0.0013 \cdot v + 0.000109 \cdot v^2$ N/kN
$F(v)$	Train motoring characteristics	$\begin{cases} 267 - 0.243 \cdot v \ kN \ (0 \le v < 160km/h) \\ 0.0021v^2 - 1.7308 \cdot v + 446.75 \ kN \ (v \ge 160km/h) \end{cases}$
$B(v)$	Train braking characteristics	$\begin{cases} 280 \cdot v/10 & kN & (0 \le v < 10km/h) \\ -0.2241v + 281.74 & kN & (10 \le v < 200km/h) \\ 0.0017v^2 - 1.5602v + 475.38 & kN & (v \ge 200km/h) \end{cases}$

At the beginning of the simulation, the program randomly generates 30 train running curves according to the principle of train running curve generation, and each firefly in the initial firefly population corresponds to a curve, and the fitness value is calculated for each individual separately, and the individual fireflies search and move their positions according to the fitness value to achieve the purpose of iteration. As the iteration of the population continued, the fireflies continuously attracted each other and shifted their positions, and the corresponding running curves also changed. The 10th, 50th, 100th, 150th, 180th and 200th generations of the population were selected in the iterative process, and the energy consumption and running time of the optimal individuals in each generation of the population were recorded to obtain **Fig. 6**, and each firefly generation was recorded separately. The performance indexes and fitness values of each generation of firefly individuals were recorded in **Table 5**, and **Fig. 7** shows the changes of fitness values of the optimal individuals in each generation of firefly populations with population iterations.

Table 5. The energy consumption and operation time of the optimal individual of each generation.

Iteration number	Energy consumption (kWh)	Running time (s)	Stop position index	Smoothness index	Fitness value
1	846.4612	1302	0.1865	0.1567	6.6852e-07
10	834.0726	1312	0.2016	0.1424	6.8931e-07
50	834.0726	1314	0.2016	0.1424	6.9086e-07
100	834.0725	1316	0.2017	0.1371	6.9096e-07
150	834.0725	1316	0.2015	0.1371	6.9096e-07
180	834.0725	1316	0.2016	0.1366	6.9107e-07
200	834.0725	1316	0.2016	0.1366	6.9107e-07

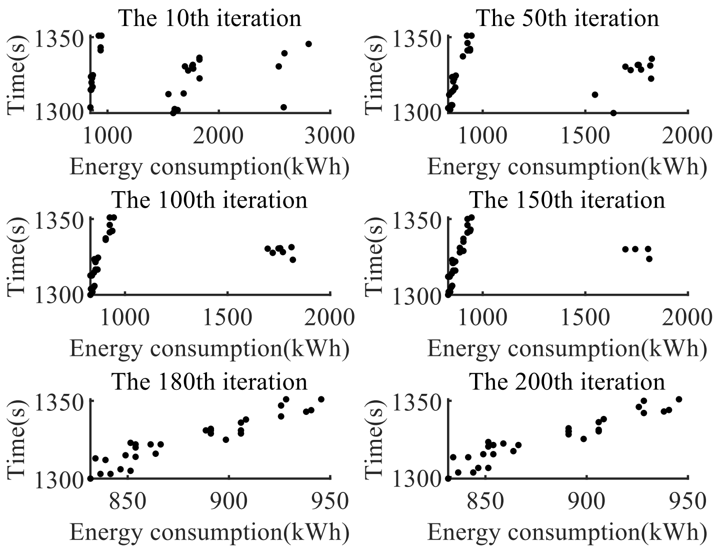

Fig. 6. Distribution of energy consumption-run time during population iteration.

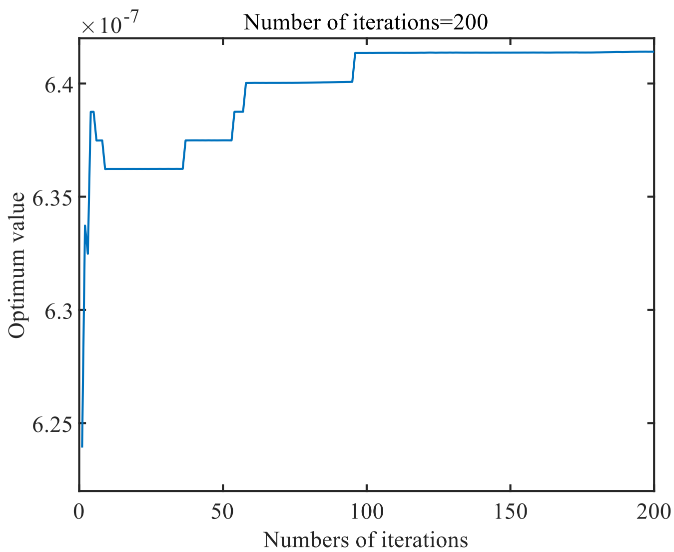

Fig. 7. Variation curve of the fitness value.

Fig. 6 depicts the distribution of energy and time consumption of each individual firefly in the population at different iterations. When the iteration is just started, the fireflies closer to each other are more likely to attract each other, and the individual fireflies have a blocky distribution in the running energy and time consumption graph. The energy consumption of the firefly population ranges from 800 to 3000 kWh, where the firefly individuals with too little energy consumption generally appear to stop too early and stopping position index is large due to additional error values, resulting in low adaptation values; the firefly individuals with too much energy consumption have too low adaptation values due to long running time. As the population continues to iterate, the individuals with larger fitness values continue to attract the individuals with weaker fitness values, and eventually the firefly individuals representing unreasonable curves no longer appear in the population, and the whole population is concentrated in the reasonable range of operating energy and time consumption values.

As can be seen from **Table 5** and **Fig. 7**, the GSO algorithm takes advantage of the population intelligence algorithm to perform several optimization solutions at the same time, and by about the 50th generation, the fitness value of the population tends to stabilize and has searched for an operating curve that reduces the operating energy consumption by approximately 12 kWh compared with the optimal solution of the initial population, and when the iteration proceeds to about the 100th generation, the fitness value of the firefly population experiences another increase, and the time consumption and fitness values both The time consumption and fitness values meet the constraint requirements and finally show a stable state with only small adjustments to the performance indicators, which laterally reflects that the algorithm has a fast convergence speed and good performance in finding the best. By the 200th generation, the population converges to the final solution.

After 200 iterations, the operation curves corresponding to the optimal individuals of the last generation population are shown in **Fig. 9(a)**, and **Figs. 9(b), 9(c)**, and **9(d)** show the train operation strategies proposed by the literature [5] using the Q-learning method and the DP algorithm, respectively, and the comparison data are shown in the table, where the train operation curves solved using the GSO algorithm, and the train operation curves solved using the training matrix number 6*10^6 times Q-learning method (6*10^6), the operation curves using the training matrix number 1*10^7 times Q-learning method (1*10^7), and the DP algorithm are compared, and the train operation energy consumption, actual train operation time, and planned train operation time data are shown in **Table 5**.

Table 6. The energy consumption and operation time of the optimal individual of each generation.

Optimization methods	Energy consumption (kWh)	Running time (s)	Planned running time (s)
DP Algorithm	1004.062	1370	1365
Q-learning Algorithm (1*10^7)	922.367	1370	1369
Q-learning Algorithm (6*10^6)	886.261	1370	1377
GSO Algorithm	834.072	1370	1316

As can be seen from **Table 6** and **Fig. 8**, compared with the DP algorithm and Q-learning algorithm, the train operation curve optimized using the GSO algorithm consumes less energy, which is more in line with the demand for energy-efficient driving and can provide research ideas for more intelligent automatic train driving in the future.

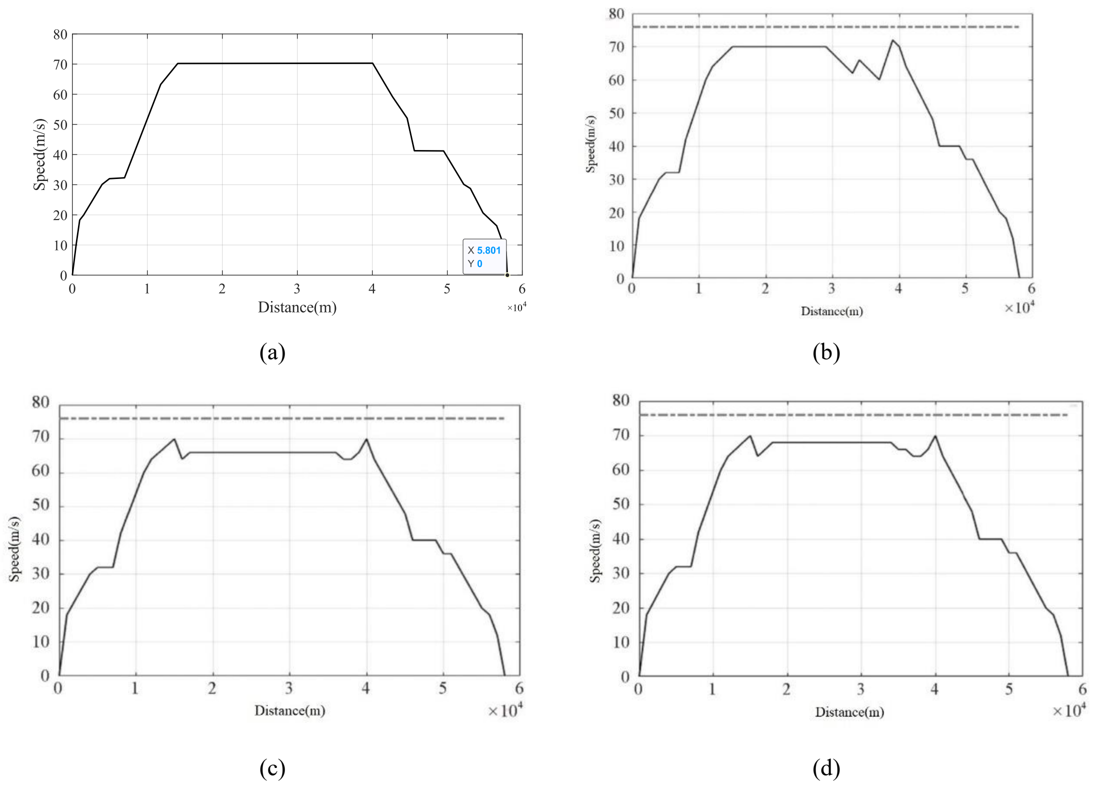

Fig. 8. (a): The running curve obtained from the solution of GSO algorithm. (b): The running curve obtained from the solution of DP algorithm. (c): The running curve obtained from the solution of the Q-learning algorithm(1× 10*7) . (d): The running curve obtained from the solution of the Q-learning algorithm(6*10^6).

6 Conclusion and Summary

The main work of this paper is to apply the GSO algorithm, a new intelligent group optimization algorithm, to the problem of energy-saving optimized operation of high-speed trains, analyze the operation process and maneuvering strategy of high-speed trains, construct four quantitative energy-saving performance index functions based on the calculation model of high-speed train traction dynamics, establish a multi-objective optimization model of the train operation curve, and design a train operation curve optimization method based on the GSO optimization algorithm. Finally, the paper shows the effectiveness of the proposed method by simulating the actual track data between Heishan North and Fuxin stations of the Beijing-Shenzhen Passenger Dedicated Line as the background. In the future, the GSO algorithm can be improved by combining more complex train operation environments, considering different speed classes of trains, and considering the energy-saving optimization problem in the case of train tracking operation.

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