IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 21, 2019, accepted August 7, 2019, date of publication August 29, 2019, date of current version September 10, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2937656

Research on Optimization of Train Energy-Saving Based on Improved Chicken Swarm Optimization

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This work was supported in part by the National Natural Science Foundation of China under Grant 51765006, in part by the Natural Science Foundation of Guangxi Zhuang Autonomous Region of China under Grant 2017GXNSFDA198012, in part by the Key Project of Science and Technology of Guangxi Zhuang Autonomous Region of China under Grant AB17195046, and in part by the Innovation Project of Guangxi Graduate Education under Grant YCSW2018033.

ABSTRACT To obtain an operation curve of a train with minimum energy-consumption and improve the utilization of regenerative braking energy without changing equipment and infrastructure, this paper proposes a new optimization method of energy-saving for a train based on an improved chicken swarm optimization algorithm after analyzing the calculation method of energy-consumption for a train and improving the chicken swarm optimization algorithm. On this basis, this paper establishes an optimization model of energy-saving for a train by taking minimum energy-consumption, accurate stopping and punctuality as optimization objectives, and solves the model with the improved chicken swarm optimization algorithm. Finally, a simulation analysis for the method proposed in this paper is performed by using MATLAB software with the running parameters of Nanning metro line 1 in China. The results of the simulation analysis show that the method proposed in this paper is effective in solving the optimization problem of train energy-saving.

INDEX TERMS Improved chicken swarm optimization, optimization of train energy-saving, optimization of train operational scheme.

I. INTRODUCTION

Energy-saving will bring many benefits to the railway transportation because it is an energy-consumption system. To ensure the low-cost of railway transportation, energy-saving has become a key issue in railway transportation industry [1]. An effective way to reduce the cost of railway transportation is improving the equipment and infrastructure of railway. However, it needs long time and high investment. Exploring an optimization strategy to reduce the energy-consumption of train without changing equipment and infrastructure is also an effective approach for reducing the cost of railway transportation, and it has become an important research topic in recent years [2].

Because of the high computational complexity and time-consuming of railway system, current optimization of energy-saving for train mainly use the combined method of offline optimization and online tracking control [3]–[5]. Offline optimization is mainly to formulate an operation curve of train according to the operation information before the train runs and online tracking control is mainly to dynamically track the operation curve of train which is optimized offline after the train runs [3]–[5]. Offline optimization is actually a nonlinear optimization problem with minimum energy-consumption as optimization objective and constrained by multiple constraints at the same time [3]–[5]. Due to the complexity and multi-constraints of such optimization problem, it is difficult to solve them by classical solutions of optimization problem, bionic algorithm, group intelligence algorithm and evolutionary algorithm, etc. have become the major solutions of such optimization problem at present [6]–[8].

With the rapid development of railway transportation, reducing the energy-consumption of train and improving the efficiency of energy has attracted great attention of scholars. At present, methods for optimizing energy-saving of train without changing equipment and infrastructure have been deeply researched by scholars, mainly focusing on improving the utilization of regenerative braking energy, improving the control method, optimizing the operational scheme and optimizing the operation curve, etc. For energy-efficient driving and energy conservation, an accurate electric traction model to optimize the operation of train between

The associate editor coordinating the review of this article and approving it for publication was Canbing Li.

stations was proposed by Zhao *et al.* in 2018, but the proposed method didn't consider the regenerative braking energy [8]. To minimize the energy-consumption of train, an energy-saving optimization method based on the multi-population genetic algorithm was researched by Lin *et al.* in 2017, but the energy-consumption from the mechanism was not analyzed by the proposed method [9]. In order to reduce energy-consumption, a scheduling and control system for automatic train operation was proposed by Watanabe *et al.* in 2018 [10]. However, the proposed method is difficult to achieve in practice because it needs to meet many assumptions. Due to the limitations of train acceleration, inertia and safety factors, the proposed method is difficult to adjust train speed quickly in practical application. Zhao *et al.* established an optimization model of energy-conservation for a single rapid transit train between stations in 2018, but the method proposed only considered the constant efficiency value of mechanical energy consumption or assumed that mechanical energy was directly converted into electrical energy consumption [8]. In order to save the energy of train, a multi-train energy-saving operation strategy was proposed by Liu and Zhao in 2017, but the method proposed only took into account the schedule time of a train [11]. In order to improve the efficiency of energy, Gao and Yang proposed a comprehensive optimization method of energy-saving method in 2019 [12]. However, the proposed method is too complex to be implemented in practical application. An energy-consumption optimization method by optimizing the stopping time of each station and optimizing the train timetable based on Pareto multi-objective genetic algorithm was proposed by Zhu *et al.* in 2017 [13]. However, the proposed method only considered the optimization of train schedule and did not essentially analyze the energy-consumption of train. To minimize the energy-consumption and reduce the traction energy, an optimization model which based on brute force algorithm and NS-GSA algorithm was proposed by Zhou *et al.* in 2018, but the computational complexity of the solution method is too high and the regenerative braking energy was not take into account in the model [14]. An energy-saving optimization method with the analysis of the cruise speed train control strategy was proposed by Yu in 2018, but it did not consider the accelerating process and breaking process of train [15]. To avoid long-duration use of braking a method with four-stage energy-saving control was proposed by Bai *et al.* in 2018 [16]. However, the proposed method was only for the braking process. Based on a common scenario that an accelerating train can reuse the regenerative energy from a braking train on an opposite track, Su *et al.* proposed a cooperative train control method to minimize the energy-consumption in 2015, but the proposed method is difficult to implement in practice because too many conditions are simplified [17]. In order to improve the energy efficiency of a timetable, Wang and Goverde proposed a approach for energy-efficient timetabling by adjusting the running time allocation of given timetables using train trajectory optimization in 2018 [18]. Although the approach proposed by Wang and Goverde provided a novel approach for energy-efficient timetabling, but it only took into account the timetable and did not take into account the optimization of operation curve and regenerative braking energy. To improve the operational efficiency and reduce the energy-consumption, a nonlinear optimal control method was proposed by Zhang *et al.* in 2018, but the proposed method only considered the optimal regulation of a train [19]. To save the energy of a train, a rescheduling method based on graphical representation was proposed by Huang *et al.* in 2018 [20]. However, the proposed method only considered rescheduling the trains, and it did not reveal the energy-consumption and energy-saving of the train radically. Cao and Liu proposed a two-stage optimization method for energy-saving in 2018, but the proposed method only considered the constraint of running time, and did not considered the constraint of traction and the constraint of acceleration [21]. In order to optimize the use of regenerative braking energy, a energy-saving optimization method that considered both minimum energy-consumption and multi-train schedule-optimization was proposed by Feng *et al.* in 2018, but the implementation of the proposed method was too complex to be achieved in practical application [22]. To reduce energy-consumption of a train, Ning *et al.* proposed a two-stage urban rail transit operation planning approach comprising running time allocation and regenerative energy utilization in 2018, but they did not provide a specific solution of the established model [23]. To minimize the energy-consumption under the premise of reducing the delay of a train, Yang *et al.* developed an energy-efficient rescheduling approach under delay perturbations for train in 2018, but the developed approach did not consider the use of the regenerative braking energy [24]. To improve energy-efficiency of a train, Liu *et al.* designed an approximate dynamic programming approach for energy-efficiency subway train scheduling problem with time-dependent demand in 2018, but they did not provide the specific solution of the approach [25]. To achieve energy-saving of train, a complex model study of trajectory combined with a matrix control algorithm was proposed by He *et al.* [26]. The proposed method which could overcome the lack of matching opportunity for overlap time was of reference significance to the study of similar optimization. However, the solution algorithm of proposed optimization model can be further improved.

In the aspect of energy-saving optimization algorithm, bionic optimization algorithm and heuristic optimization algorithm have been researched by many scholars and achieved many results in recent years. To attain the minimal number of phasor measurement units to access an observable power system, Nazari-Heris *et al.* provided a literature review on different heuristic optimization methods to solve the optimization problem [27]. In order to solve the optimization problem of combined heat and power economic dispatch, a comprehensive review on application of heuristic optimization algorithms for the solution of combined heat and power economic dispatch problem is provided by Nazari-Heris *et al.* [28]. To solve the optimization problem of generation scheduling of hydro-based power units, a comprehensive review on the application of heuristic methods to obtain optimal generation scheduling of hydrothermal systems was provided by Nazari-Heris *et al.* [29]. Although these optimization methods have achieved many excellent results, they are not suitable for energy- saving optimization of train operation with multiple constraints. An effective cuckoo search algorithm proposed by Nguyen *et al.* has been succeed to solute the problem of the problem of combined heat and power economic dispatch [30]. However, the proposed algorithm did not solve the disadvantage of weak local search ability of the algorithm itself. In order to solve the optimization problem of combined heat and power economic dispatch, a novel multi-player harmony search method was proposed by Nazari-Heris *et al.* [31]. The proposed method has important reference value for solving the optimization problem of large-scale scheduling. In order to solve the problem of energy-saving optimization, an updated review and analysis of harmony search algorithm was provided by Nazari-Heris *et al.* [32]. The advantage of harmony search algorithm was that it was relatively simple to implement and required less parameters of the algorithm. However, the ability of the algorithm to solve the energy-saving optimization problem with multi-objectives was not outstanding.

The optimization of energy-saving for train has been researched by many scholars, and some results have been achieved. However, many methods proposed by scholars were difficult to achieve the desired results in practical application because the researches did not consider both the energy-consumption and the regenerative breaking energy of a train or ignored the limitation of the solution to the problem. For this reason, this paper will research a new method based on chicken swarm optimization to optimize energy-saving for a train with considering both the energy-consumption and the regenerative breaking energy.

To achieve the energy-saving of a train without changing the existing equipment and infrastructure, it is very necessary to explore a new optimization method of energy-saving for a train. Formulating a good operation curve of a train with considering both the energy-consumption and regenerative breaking energy of a train is the key to optimize the energy-saving of a train, and the key to formulate a good operation curve of a train with minimum energy-consumption is to find appropriate switching points of operation conditions. This paper will base on an improved chicken swarm optimization to research on a method of finding appropriate switching points of operation conditions to optimize the energy-saving of a train with considering both the energy-consumption and regenerative breaking energy of a train.

II. SYMBOLS

Symbol	Unit	Description
x_{ij}^t		Position of individual i in the dimension j space after t times foraging
$rand(0, \sigma^2)$		A real number randomly extracted from a Gaussian distribution with a mean value of 0 and standard deviation of sigma σ^2
$rand$		A real number randomly extracted from a distribution between 0 and 1
$conf$		A weight coefficient
w_b	N/kN	Unit basic resistance
c_1		An empirical constant
c_2		An empirical constant
c_3		An empirical constant
v	km/h	Speed of the train
w_c	N/kN	Unit tunnel-additional resistance
L	m	Length of a tunnel
w_r	N/kN	Unit curve-additional resistance
Q		A constant
R	m	Radius of a curve
w_p	N/kN	Unit ramp-additional resistance
W	kN	Motion resistance of train
P	t	Mass of passengers, $1t = 1000kg$
G	t	Empty mass of train, $1t = 1000kg$
F_i		Inertial factor
g	$N \cdot m$	Gravity acceleration
S	m	Distance between two stations
Δs_i	m	The i^{th} small segment discretized from the distance between two stations
$\overline{w_b}$	N/kN	Average unit basic resistance
$\overline{W_i}$	kN	Average motion resistance
$\overline{v_i}$	km/h	Average speed of train in Δs_i
ΔE_i	kJ	Energy-consumption of train in Δs_i
v_{is}	km/h	Starting speed of train in Δs_i
v_{ie}	km/h	Terminal speed of train in Δs_i
a_i	m/s^2	Acceleration of train in Δs_i
Δt_i	s	Running time of train in Δs_i
η		Conversion-efficiency of regenerative braking energy
N		Total small segments discretized from the distance between two stations
v_{reg}	km/h	Dividing speed for regenerative braking and non-regenerative braking
Φ		Objective function of optimization model
T	s	Planned running time between the two stations
$a_{\max}$	m/s^2	Maximum acceleration allowed for train
$v_{\max}$	km/h	Maximum speed allowed for train
$fitness$		Fitness of chicken fitness in the chicken swarm optimization
K_i		Penalty factor, when the acceleration violates the control regulation of the train in Δs_i
Z_i		Penalty factor, when the acceleration violates the maximum acceleration allowed for the train in Δs_i
ρ		A constant
ε		A constant
$E_{\max}$	kJ	Maximum energy-consumption between two stations
N_T		Number of traction motor
P_T	kW	Power of traction motor
T_{total}	s	Actual running time between the two stations

III. CHICKEN SWARM OPTIMIZATION

A. BASIC CHICKEN SWARM OPTIMIZATION

Chicken swarm optimization is a global optimization algorithm, which simulates the law of chicken foraging abstractly and integrates the advantages of genetic algorithm, particle swarm optimization algorithm and bat algorithm, was proposed by Meng *et al.* [33]. Chicken swarm optimization simulates the behavior of chicken group according to different rules, the grading system of the chicken group, the competition among the chicken group, the hatchery of the hen, and the growth of chick [33], [34]. The algorithm has become a prominent research topic in scientific research, and it provides a new solution for solving the problem of global optimization in the fields of computing, engineering and management science, etc. [34]. There is a strict hierarchy of chicken group during an actual foraging process. In the foraging process, the individuals in the chicken group are graded into rooster, hen, and chick. In the chicken group, the hen follows the rooster for foraging, whereas the chick forages around the hen. Therefore, the rooster plays a leading role in the chicken group, and it has the most advantage in the process of the foraging competition. The chick with poor foraging ability in the chicken group can only follows the hen to forage. The dominant performance of each individual in the chicken group is determined by the fitness function corresponding to the target function in its position. To reflect the behavior of the hen hatchery and the chick growing into a rooster or a hen, chicken swarm optimization will grade each chick according its fitness after completing the foraging. After being graded, the individuals in the chicken group initiate a new foraging behavior based on the position updated formula until meeting the termination condition. After chicken swarm optimization completes calculating, the position of the best individual in the chicken group is the optimal solution of the optimization.

We suppose the solutions space of problem is D dimensions, total number of individuals in the chicken group is *popNum*, number of roosters is *rNum*, number of hens is *hNum*, and number of chickens is *cNum*. Therefore, the foraging behavior of the roosters, hens, and chickens is as follows.

1) THE FORAGING BEHAVIOR OF A ROOSTER

Supposing the position of rooster i is $x_{ij}^t (i = 1, 2, \ldots, rNum; j = 1, 2, \ldots, D)$ after t times foraging in the dimension j space, then it is updated as follows after $t+1$ times foraging.

$$x_{ij}^{t+1} = x_{ij}^t + x_{ij}^t \cdot rand(0, \sigma^2) \tag{1}$$

$$\sigma^2 = \begin{cases} 1, & if\ f_i \le f_k \\ \exp\left(\dfrac{f_i - f_k}{|f_i| + \varepsilon}\right), & others \end{cases} \tag{2}$$

$$k = [1, rNum], \quad k \ne i \tag{3}$$

In the formula, $rand(0,\sigma^2)$ is a real number randomly extracted from a Gaussian distribution with a mean value of 0 and standard deviation of sigma σ^2, k is any rooster except rooster i, f_i is the fitness of rooster i, f_k is the fitness of the rooster k, and ε is a constant.

2) THE FORAGING BEHAVIOR OF A HEN

Supposing the position of hen i is $x_{ij}^t (i = 1, 2, \ldots, hNum; j = 1, 2, \ldots, D)$ after t times foraging in dimension j space, it is updated as follows after $t+1$ times foraging.

$$x_{ij}^{t+1} = x_{ij}^t + \exp\left(\frac{f_i - f_r}{|f_i| + \varepsilon}\right) \cdot rand \cdot (x_{rj}^t - x_{ij}^t) + \exp(f_p - f_i) \cdot rand \cdot (x_{pj}^t - x_{ij}^t) \tag{4}$$

In the formula, *rand* is a real number randomly extracted from a distribution between 0 and 1, r is the spouse of hen i, p is any rooster except rooster r, f_i is the fitness of hen i, f_r is the fitness of rooster r, and f_p is the fitness of rooster p.

3) THE FORAGING BEHAVIOR OF A CHICK

Supposing the position of hen i is $x_{ij}^t (i = 1, 2, \ldots, cNum; j = 1, 2, \ldots, D)$ after t times foraging in dimension i space, it is updated as follows after $t+1$ times foraging.

$$x_{ij}^{t+1} = x_{ij}^t + conf \cdot (x_{mj}^t - x_{ij}^t), \quad conf \in [0, 2] \tag{5}$$

In the formula, m is the hen followed by chicken i, and *conf* is a weight coefficient.

B. IMPROVED CHICKEN SWARM OPTIMIZATION

Chicken swarm optimization is a global optimization algorithm which integrates the advantages of genetic algorithm, particle swarm optimization algorithm and bat algorithm. Its global search ability is very strong, but the method of updating the position of chickens in chicken swarm optimization results in the blindness of algorithm search due to lacking of guidance on search direction. So, improving the updating formula of chicken position is a necessary way to improve the performance of chicken swarm optimization.

In the basic chicken swarm optimization, the updating formula of chicken position only learns from the position of a hen which is followed by the chicken, resulting in weakening the optimization performance of algorithm to a certain extent and reducing the convergence speed of algorithm. In order to improve the global optimization performance of algorithm and the convergence speed of algorithm effectively, the updating formula of chicken position is improved in this paper. After being improved, the position of a chicken not only refers to the position of the hen but also refers to the position of the rooster around it.

Supposing the position of a chicken i is $x_{ij}^t (i = 1, 2, \ldots, cNum; j = 1, 2, \ldots, D)$ after t times foraging in dimension j space, the formula for updating position of a chicken is as follows according to the principle of the improved chicken swarm optimization.

$$x_{ij}^{t+1} = x_{ij}^t + \exp\left(\frac{f_i - f_m}{|f_i| + \varepsilon}\right) \cdot rand \cdot (x_{mj}^t - x_{ij}^t) + \exp\left(\frac{f_i - f_r}{|f_i| + \varepsilon}\right) \cdot rand \cdot (x_{rj}^t - x_{ij}^t) \tag{6}$$

In the formula, m is the hen followed by chicken i, r is the rooster followed by chicken i, *rand* is a real number randomly extracted from a distribution between 0 and 1, f_i is the fitness of chicken i, f_m is the fitness of hen m, f_r is the fitness of rooster r, and ε is a constant.

IV. THEORETICAL BASIS OF THE OPTIMIZATION MODEL

The motion resistance of train is mainly reflected in the friction between the parts, surface of train and air, wheel and rail, etc. It is mainly composed of the basic resistance of train, curve-additional resistance, ramp-additional resistance, air-additional resistance, etc. Because of complex factors, it is difficult to calculate the basic resistance of train accurately with theory. In practice, it is usually calculated by the gravity of the train and the unit basic resistance of motion which can be estimated by an empirical formula as follows [35].

$$w_b = c_1 \cdot v^2 + c_2 \cdot v + c_3 \tag{7}$$

In the above empirical formula, c_1, c_2, and c_3 are empirical parameters without a unit, and v is the speed of train with a unit of km/h. After the train enters the tunnel, the fast-running train reduces the cross-sectional area of air flow and the train is obstructed by the rapid air impact force on it, resulting in tunnel-additional resistance which is related to tunnel length, tunnel cross-sectional area train speed and train shape, etc. At present, it is not mature to calculate tunnel-additional resistance theoretically, and empirical formula or experimental data is usually used to estimate it. Tunnel-additional resistance is usually calculated by the gravity of train and the unit tunnel-additional resistance which can be obtained from an empirical formula as follows [35].

$$w_c = \begin{cases} L \cdot v^2 \cdot 10^{-7}, & \textit{ramp in tunnel} \\ 0.00013L, & \textit{others} \end{cases} \tag{8}$$

When there is restricted ramp in tunnel $w_c = L \cdot v^2 \cdot 10^{-7}$, others $w_c = 0.00013L$. When the train runs on a curved track, the curved track will drag the train, resulting in curve-additional resistance. Due to complex factors, curve-additional resistance is also difficult to be calculated accurately with theory, and it is usually calculated by the gravity of train and the unit curve-additional resistance. The value of unit curve-additional resistance can be obtained from the following empirical formula [36].

$$w_r = \frac{Q}{R} \tag{9}$$

When the train runs on a slope, there is a gravity component of the train along the track, resulting in ramp-additional resistance. Ramp-additional resistance is usually calculated by the gravity of train and the unit ramp-additional resistance which can be estimated by an empirical formula. In consideration of the basic resistance, tunnel-additional resistance, curve-additional resistance and ramp-additional resistance, the motion resistance of train can be calculated by a formula as follows [34].

$$W = (w_b + w_c + w_r + w_p) \cdot (P + G) \cdot g \cdot 10^{-3} \tag{10}$$

In order to facilitate the analysis of train kinematics, the distance between the stations is discretized into small segments in this paper. Supposing the distance between two stations is S, the length of each small segment can be calculated by the following formula.

$$\Delta s_i = \frac{S}{N} (i = 1, 2, \ldots, N) \tag{11}$$

When Δs_i is small enough, the instantaneous motion resistance of train can be replaced by the average motion resistance of train in Δs_i, and the average motion resistance can be calculated by a formula as follows.

$$\overline{w_b} = c_1 \cdot \overline{v_i}^2 + c_2 \cdot \overline{v_i} + c_3 \tag{12}$$

$$\overline{W} = (\overline{w_b} + w_c + w_r + w_p) \cdot (P + G) \cdot g \cdot 10^{-3} \tag{13}$$

The train accelerates under the action of traction force and motion resistance in the process of traction. Due to the long distance between two stations and existing of complex factors, it is difficult and complicated to analyze the change of kinetic energy directly. For this reason, this paper takes the analysis of small segment to approximate the analysis of long distance by discretizing the distance between two stations into many small segments. When a segment is small enough, the energy-consumption of train in Δs_i can be calculated by the following formula.

$$\Delta E_i = W_i \cdot \Delta s_i + \frac{(P + G \cdot F_i) \cdot (v_{ie}^2 - v_{is}^2)}{2 \cdot 3.6^2} \tag{14}$$

The keeps a constant speed under the action of the traction force and motion resistance in the process of cruising, and the energy-consumption of train in Δs_i can be calculated by the following formula.

$$\Delta E_i = \overline{W_i} \cdot \Delta s_i \tag{15}$$

The train decelerates under the action of motion resistance in the process of coasting, and the energy-consumption of train in Δs_i can be calculated by the following formula.

$$\Delta E_i = 0 \tag{16}$$

In the process of braking, the train decelerates under the action of braking force and motion resistance. When the speed of the train is greater than or equal to v_{reg}, the train can be used regenerative braking to decelerate, and the energy-consumption of train in Δs_i can be calculated by the following formula.

$$\Delta E_i = -[\frac{(P + G \cdot F_i) \cdot (v_{is}^2 - v_{ie}^2)}{2 \cdot 3.6^2} - \overline{W_i} \cdot \Delta s_i] \cdot \eta \tag{17}$$

In the above formula, ΔE_i is a negative number relative to the energy-consumption because power is generated in the process of regenerative braking. When the speed of train is less than v_{reg}, the train can be used air braking or other non-regenerative braking to decelerate, and the energy-consumption of train in Δs_i can be calculated by the following formula.

$$\Delta E_i = 0 \tag{18}$$

To facilitate the analysis of the train movement, the entire train is regarded as a single point system. The motion equation of the train in Δs_i is as follows.

$$v_{ie} = v_{is} + 3.6 \cdot a_i \cdot \Delta t_i \tag{19}$$

$$\Delta s_i = \frac{v_i \cdot \Delta t_i}{3.6} + \frac{1}{2} \cdot a_i \cdot \Delta t_i^2 \tag{20}$$

$$a_i = \frac{v_{ie}^2 - v_{is}^2}{2 \cdot 3.6^2 \cdot \Delta s_i} \tag{21}$$

V. THE MODEL AND SOLUTION OF THE OPTIMIZATION

A. THE FORMULATION OF THE MODEL

A train usually follows a specified timetable, which requires a train to leave from a station at a certain time and arrive at the other station on time. According to the train operational scheme, the running time and distance between two stations are fixed. The operation of train can be divided into four working processes which include traction, cruising, coasting and braking. Energy is consumed to make the train speed up in the process of traction and energy is consumed to make the train run at a constant speed in the process of cruising, when the train runs in the processes of coasting and braking without energy-consumption.

In order to make the train run from one station to another with minimum energy-consumption, it is obvious that the energy-consumption of train in the processes of traction and cruising should be optimized. Due to the basic requirements of operational scheme, the accurate stopping and the punctuality should be considered at the same time when the minimum energy-consumption is considered. Therefore, the optimization problem of train energy-saving becomes a multi-objective optimization in which accurate stopping, punctuality and minimum energy-consumption are considered under the multiple constraints of time, distance, speed, etc.

In order to reduce the complexity of establishing the optimization model of train energy-saving, this paper does not consider the limitation of the maximum traction effort of motors, and supposes the motors have enough traction effort under the maximum acceleration of train. Due to the long distance and the existence of various uncertainties, it is difficult to establish the optimization model of train energy-saving between two stations directly. Therefore, this paper takes the analysis of small segments to approximate the analysis of long distance between two stations by discretizing the distance into n small segments. On this basis, this paper establishes an optimization model of train energy-saving by taking the acceleration and speed of train as constraints and taking minimum energy-consumption, accurate stopping and punctuality as objectives. The objective function and constraint conditions of the optimization model are as follows.

$$\begin{aligned} \min \Phi = \alpha \cdot \left(\sum\nolimits_{i=1}^{n} \Delta t_i - T\right)^2 + \beta \cdot (v_{ne} - 0)^2 \\ + \gamma \cdot \sum\nolimits_{i=1}^{n} \Delta E_i \end{aligned}$$

$$s.t. \begin{cases} \Delta s_i = \dfrac{S}{N} \\ a_i = d\dfrac{v_{ie}^2 - v_{is}^2}{2 \cdot 3.6^2 \cdot \Delta s_i} \\ \Delta t_i = \begin{cases} \frac{v_{ie}-v_{is}}{3.6 \cdot a_i}, & if\ v_{ie} \neq v_{is} \\ \frac{T}{n}, & others \end{cases} \\ 0 \le v_{is} \le v_{\max} \\ 0 \le v_{ie} \le v_{\max} \\ |a_i| \le |a_{\max}| \\ v_{1s} = 0 \\ i = 1, 2, \ldots, n \end{cases} \tag{22}$$

In the model of optimization, α, β and γ represent weight coefficient of real running time, weight coefficient of accurate stopping and weight coefficient of energy-consumption, respectively. α,β and γ are combined parameters in the optimization model, which indicate that the degree of importance attached to energy-consumption, punctuality and accurate stopping, respectively. α,β and γ are all in the range of 0 to 1, and the sum of them is equal to 1. The values of α,β and γ are determined by the concern degree of the optimization sub problem. Since α,β and γ are combined parameters, their values can be obtained by the grid search algorithm which uses a brute-force approach to find optimal parameters. These three parameters have an important influence on the optimization results. For example, if we pay more attention to the role of energy-consumption in the optimization model, then the value of γ should be larger than others, otherwise its value is smaller than others. Because this paper pays more attention to energy-consumption, the values of α, β and γ are taken 0.35, 0.1 and 0.55 after being optimized by the grid search algorithm, respectively.

B. THE SOLUTION APPROACH

The optimization of train energy-saving is a complex optimization problem with nonlinear constraints and without optimization law of mathematical analysis. For such complex optimization problem, chicken swarm optimization provides a new and effective approach for solving them. Chicken swarm optimization is a global optimization algorithm, which simulates the law of chicken foraging abstractly and integrates the advantages of genetic algorithm, particle swarm optimization algorithm and bat algorithm. Chicken swarm optimization algorithm has become a prominent research topic in scientific research, and it provides a new solution for solving the problem of global optimization in the fields of computing, engineering and management science. A chicken swarm optimization algorithm improved in this paper not only retains the strong global optimization ability of the original algorithm, but also overcomes the blindness of local search. In view of the advantages of the strong search ability of the improved chicken swarm optimization algorithm which is proposed in this paper, it is taken to solve the model of optimization in this paper.

It is known from the model of optimization, the variable to be optimized is the endpoint speed of each segment. The key to solve the model of optimization is to find a vector consisting of a series of endpoint speed of each small segment. According to the improved chicken swarm optimization algorithm and the key to solve the model of optimization, the position of the individual in chicken group is represented as follows.

$$x = (v_{1s}, \ldots, v_{is}, \ldots, v_{Ne}) \tag{23}$$

It is known from the principle of discretizing the distance between two stations, the terminal speed of train in Δs_i equals the starting speed of train in Δs_{i+1}, that is $v_{ie} = v_{i+1s}$. Because the calculation result of energy-consumption may be very large when the time value may be very small, this paper normalizes variables before calculating the fitness in the improved chicken swarm optimization algorithm to avoid the phenomenon of eating decimals which results in the instability of numerical calculation. T, v_{max} and E_{max} are used to normalize time value, speed value and energy value, respectively. Finally, the formula of calculating the fitness in the improved chicken swarm optimization is as follows.

$$fitness = \frac{1}{(\prod_{i=1}^{N} K_i) \cdot (\prod_{i=1}^{N} Z_i) \cdot f_b + \varepsilon} \tag{24}$$

$$f_b = \alpha \cdot (\frac{\sum_{i=1}^{N} \Delta t_i}{T} - 1)^2 + \beta \cdot (\frac{v_{Ne}}{v_{\max}} - 0)^2 + \gamma \cdot \frac{\sum_{i=1}^{N} \Delta E_i}{E_{\max}} \tag{25}$$

$$K_i = \begin{cases} \rho, & a_{i-1} > 0 \ \ and \ a_i < -\dfrac{W}{(P+G)} \\ 1, & others \end{cases} \tag{26}$$

$$Z_i = \begin{cases} \rho, & if \ \ |a_i| > |a_{\max}| \\ 1, & others \end{cases} \tag{27}$$

$$E_{\max} = N_T \cdot P_T \cdot T_{total} \tag{28}$$

The process of solving the optimization model of train energy-saving based on the improved chicken swarm optimization is as follows.

(1) Number of small segments N, population size *popNum*, max generation *nMaxGeneration* are set;

(2) Based on whether v_{1s} equals 0 and v_{is} is less than $v_{\max}$, v_{2s} to v_{ne} are initialized with a random number, and v_{1s} to v_{ne} are encoded as the position of a chicken in the improved chicken swarm optimization, i.e.;

(3) a_i is calculated from v_{is}, v_{ie} and Δs_i, and then Δt_i and ΔE_i are calculated, i.e.;

(4) The chicken fitness is calculated and sorted, and the best chick is recorded;

(5) According to the chicken fitness, the chicken is graded;

TABLE 1. Parameters of train operation.

Symbol	Value	Unit
G	219.1	t
P	108.18	t
S	1725	m
$a_{\max}$	1.2	m/s^2
$V_{\max}$	80	km/h
T	100	s
P_T	220	kW

TABLE 2. Parameters of simulation and analysis.

Symbol	Value
w_c	1725
w_r	1.02
w_p	80
c_1	0.69
c_2	0.0063
c_3	0.00015
N	10
α	0.35
β	0.1
γ	0.55
$popNum$	1000
$nMaxGeneration$	1000
η	0.5
v_{reg}	8
$conf$	0.8
ε	0.000001

(6) The position of the chicken is upgraded by different formulas;

(7) It is determined whether the iteration reaches *nMaxGeneration*; if so, step (8) is followed, otherwise, step (3) is followed;

(8) The variable x of chicken position is decoded, and the best speed sequence of the train is obtained.

VI. AN APPLICATION CASE STUDY

A simulation analysis for the method proposed in this paper is performed by using MATLAB software with the running parameters of Nanning metro line 1 in China. The operation parameters of train are listed in Table 1, and the parameters of simulation and analysis are listed in Table 2. The distance between two stations in this case is 1725 m. Considering the actual ramp and curve, the maximum speed allowed for the train is 80 km/h. The running time of train is 100.4 s and the energy-consumption of train is 71842 kJ before the

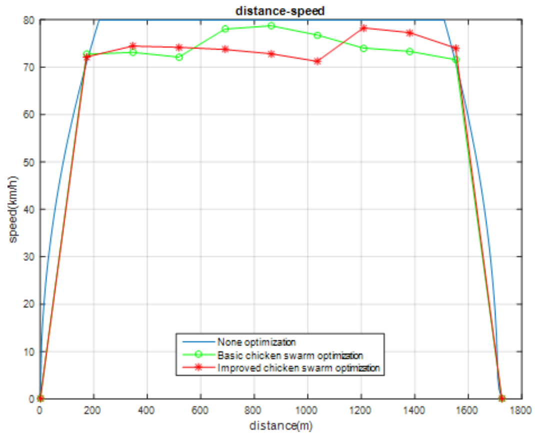

FIGURE 1. Distance and speed curve.

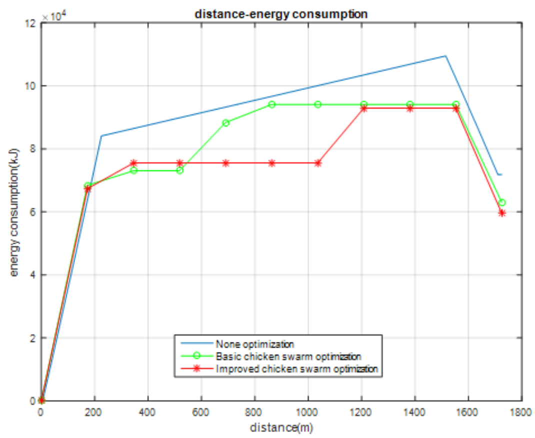

FIGURE 2. Distance and energy curve.

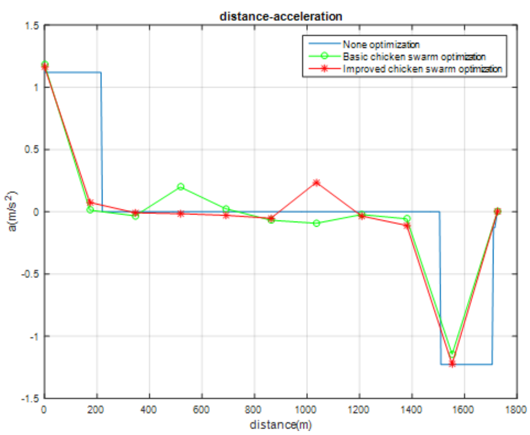

FIGURE 3. Distance and acceleration curve.

operation curve of train is optimized. In this work, methods without optimization, with the basic chicken swarm optimization, and with the improved chicken swarm optimization are used to analyze the energy-consumption of train. The distance–speed, distance–energy, and distance–acceleration curves obtained from the results of each optimization method are shown in Figures 1–3, respectively. Five analyses were carried out by the basic chicken swarm algorithm and the improved chicken swarm algorithm, the optimization results of each method are shown in Table 3 and Table 4. Comparison of the best optimization results of each method are listed in Table 5.

TABLE 3. Five times optimization results of basic chicken swarm optimization.

NO.	Time	Energy	Decrease
1	98.2 s	63910 kJ	11.04%
2	100.9 s	62941 kJ	12.39%
3	97.6 s	64660 kJ	10.00%
4	100.5 s	63141 kJ	12.11%
5	99.1 s	63490 kJ	11.63%

TABLE 4. Five times optimization results of improved chicken swarm optimization.

NO.	Time	Energy	Decrease
1	99.6 s	60290 kJ	16.08%
2	100.5 s	59905 kJ	16.62%
3	99.3 s	60662 kJ	15.56%
4	100.8 s	59520 kJ	17.15%
5	98.9 s	60903 kJ	15.23%

TABLE 5. The best optimization results of each method.

Method	Time	Energy	Decrease
No optimization	100.4 s	71842 kJ	0%
Basic chicken swarm optimization	100.9 s	62941 kJ	12.39%
Improved chicken swarm optimization	100.8 s	59520 kJ	17.15%

The running time of train is 100.4 s and the energy-consumption of train is 71842 kJ before the operation curve of train is optimized. After the operation curve of train is optimized by the basic chicken swarm optimization, the running time of train is 100.9 s and the energy-consumption of train is 62941 kJ, i.e., the energy-consumption of train is decreased by 12.39% compared to that in the case without optimization. After the operation curve of train is optimized by the improved chicken swarm optimization, the running time of train is 100.8 s and the energy-consumption of train is 59520kJ, i.e., the energy-consumption of train is decreased by 17.15% compared to that in the case of no optimization.

The total length of Nanning Rail Transit Line 1 is 32.1 km, and the operating time is 6:30-23:00. If the optimization results are extended to the whole line and the local electricity price is 0.65 yuan, the whole line can save about 4.97 million yuan in one year after being optimized by the basic chicken swarm optimization algorithm, and the whole line can save about 6.89 million yuan in one year after being optimized by the improved chicken swarm optimization algorithm.

VII. CONCLUSION

Since formulating a good operation curve of train with considering both energy-consumption and regenerative breaking energy is the key to optimize train energy-saving, an optimization method of formulating operation curve of train with considering both the energy-consumption and regenerative breaking energy of train is proposed in this paper, and an optimization model of train energy-saving is established by taking the acceleration and speed of train as constraints and taking minimum energy-consumption, accurate stopping and punctuality as objectives. Since the key to formulate a good operation curve of train with minimum energy-consumption is to find appropriate switching points of operation conditions, a method of finding appropriate switching points of operation conditions based on an improved chicken swarm optimization is researched, and it is applied to solve the optimization model of train energy-saving which is established in this paper.

With integrating the advantages of genetic algorithm, particle swarm optimization algorithm and bat algorithm, chicken swarm optimization is an effective method for solving the problem of global optimization. An improved chicken swarm optimization which is proposed in this paper can avoid falling into local optimal solution, showing better performance than the basic, and it provides a new and effective approach for solving the optimization model of train energy-saving with nonlinear constraints and without optimization law of mathematical analysis.

Finally, a simulation analysis for the method proposed in this paper is performed with the running parameters of Nanning Metro Line 1 in China. The application case-study of train operation between the Shi Bu station and Nanning Vocational & Technical College in Nanning Metro Line 1 shows that the energy-consumption of train decreases by 17.15% after the operation curve of train is optimized by the method proposed in this paper.

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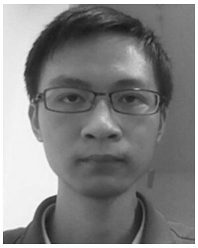

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