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FA-based Optimal Strategy Study of Train's Energy Saving Operation under Disturbed Condition

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Abstract. Different from changeable chromosome length genetic algorithm, a new method based on firefly optimization algorithm is put forward to search a train's energy saving operation strategy under running disturbance condition in railway network. The algorithm is designed and validated using a referenced simulation case. Compared with other methods, it demonstrates this new FA-based algorithm has a better result in computation efficiency and may be considered to use in other energy efficient train operation models.

Introduction

Energy consumption is one of core indexes both for the transportation industry and for society in general [1]. Although railway transportation system is considered to be more energy efficient than most other transportation systems, the issue of raising energy efficiency for railways will not be neglected to further reduce their contribution to climate change. Energy efficiency for railways includes saving energy consumption and this will reduce energy costs and emissions of pollutants.

In theory and practice, searching energy saving train operation strategies to reduce energy consumption of train traction is considered an effective way. In this field, there're a lot of studies including theoretical models and solution algorithms done in various cases [2-4]. Among these models and algorithms, an energy consumption model based on control mode sequence under disturbed condition in railway network is put forward and a random search method called changeable chromosome length genetic algorithm is often used to solve the model [5].

However, this GA-based method can't assure searching global optimal solution, and a long time is taken for its computation. So, we make an attempt to solve the energy consumption model using other intelligent optimization methods. Considering firefly algorithm optimization method simplicity and easy implementation, a FA-based algorithm which can handle multiple control mode sequences is designed to solve the energy consumption model under disturbed condition.

Energy Saving Train Operation Model and Solution Algorithm under Disturbed Condition

Energy Consumption Optimization Model under Disturbed Condition

The energy consumption optimization model under disturbed condition [5] can be formulated as follows:

Objective function: minimize $\mathrm{E} = \sum \Delta \mathrm{E}$. (1)

Subject to:

Time step constraint $n = T / \Delta t$, $\Delta t = t_{i+1} - t_i$ (2)

Speed constraint $0 \le v_i \le V_{\max}$, $v_0 = 0$, $v_n = 0$ (3)

Distance constraint $0 \le s_i \le S$, $s_0 = 0$, $s_n = S$ (4)

Time constraint $0 \le t_i \le T, t_0 = 0, t_n = T,\ \mathrm{t_d} \notin [\mathrm{a,b}]$ (5)

Control mode shift constraint: The shift between different control modes is not arbitrary and it must meet some shift rules such as traction mode can't be exchanged directly.

Where Δt is a time step, assuming there are n time steps in the train movement, v_i is initial speed for ith time step, $V_{\max}$ is the limited speed, s_i is the position for ith time step, t_i is the time of ith time step, $\mathrm{t_d}$ is the time point when this train reaches the prohibited station under disturbed condition.

According to the train movement equation, unit force and acceleration speed can be calculated for every time step, and so are for speed v, position s and energy consumption E as below.

$$v_{i+1} = v_i + a \cdot \Delta t\ . \tag{6}$$

$$s_{i+1} = s_i + \left(v_i \cdot \Delta t + \frac{1}{2} \cdot a \cdot \Delta t^2 \right) \Big/ 0.06\ . \tag{7}$$

$$\mathrm{E_{i+1}} = \mathrm{E_i} + \Delta \mathrm{E}\ . \tag{8}$$

In the above equations, E_i is the accumulated energy consumption in the ith time step, E_{i+1} is the accumulated energy consumption in the (i+1)th time step, ΔE is the energy consumption in the ith time step. The detailed computation formulations of $\mathrm{a}, \Delta \mathrm{E}$ can be given according to different locomotives.

Obviously, this model is a non-linear dynamical optimization problem with constraints. In order to solve it, it can be converted into a non-linear optimization problem without constrains using penalty function like that:

$$\text{Minimize}\ \mathrm{J} = \mathrm{E} + \alpha[\mathrm{v_e} - 0]^2 + \beta[\mathrm{s_e} - \mathrm{S}]^2 + \gamma[\mathrm{t_e} - \mathrm{T}]^2 + \lambda \mathrm{P}(\mathrm{t_d}) \tag{9}$$

Where $\mathrm{v_e}, \mathrm{s_e}, \mathrm{t_e}$ is the speed, position and time respectively when optimization calculation is finished and $\alpha, \beta, \gamma, \lambda$ are penalty factors. $\mathrm{P}(\mathrm{t_d})$ is the function of variable $\mathrm{t_d}$. If $\mathrm{t_d} \notin [\mathrm{a,b}], \mathrm{P}(\mathrm{t_d}) = 0$; else $\mathrm{P}(\mathrm{t_d}) = 1$.

Although the analytical solution can't be found directly, searching critical control mode shift position in the train movement is possible. So the problem solution can be represented as $X = (x_1, \cdots, x_i, \cdots, x_m)$, x_i is the train critical control mode position, $0 < x_1 < \cdots < x_i < \cdots < x_m < S$.

FA-based Algorithm to Search Energy Saving Train Operation Strategy[6-8]

(1) Firefly Algorithm Description

As a metaheuristic, nature-inspired, optimization algorithm, FA (Firefly Algorithm) was developed by Dr. Xin-She Yang at Cambridge University in 2007. Although the firefly algorithm has many similarities with other algorithms such as PSO, it is indeed much simpler both in concept and implementation. Its main advantage is the fact that it uses mainly real random numbers, and it is based on the global communication among the swarming particles (i.e., the fireflies).

(2) Attractiveness

In the firefly algorithm, the form of attractiveness function of a firefly is the following monotonically decreasing function:

$$\beta(\mathrm{r}) = \beta_0^* \exp(-\gamma \mathrm{r}^{\mathrm{m}}), \text{ with } \mathrm{m} \ge 1, \tag{10}$$

Where, r is the distance between any two fireflies, β_0 is the initial attractiveness at $\mathrm{r} = 0$, and γ is an absorption coefficient which controls the decrease of the light intensity.

(3) Distance

The distance between any two fireflies i and j, at positions $\mathrm{x_i}$ and $\mathrm{x_j}$, respectively, can be defined as a Cartesian or Euclidean distance as follows:

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \text{ , with } m \geq 1 \tag{11}$$

Where, x_i is the kth component of the spatial coordinate x_i of the ith firefly and d is the number of dimensions. For different d, distance can be different such as Manhattan distance or Mahalanobis distance.

(4) Movement

The movement of a firefly i which is attracted by a more attractive firefly j is giben by the following equation [8,10]:

$$x_i = x_i + \beta_0 \exp(-\gamma r_{ij}^2) * (x_j - x_i) + \alpha * (\text{rand} - 0.5) \tag{12}$$

Where the first term is the current position of a firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies, and the third term is used for the random movement of a firefly in case there are not any brighter ones. The coefficient α is a randomization parameter determined by the problem of interest, while rand is a random number generator uniformly distributed in the space [0,1]. As in this implementation of the algorithm, we will use $\beta_0 = 1.0, \alpha \in [0,1]$ and the attractiveness or absorption coefficient $\gamma = 1.0$, which guarantees a quick convergence of the algorithm to the optimal solution.

Simulation Case Study

Case Description

To confirm this PSO-based algorithm's validity, a simulation case is studied and compared. The line data [5] is depicted in Fig.1, *AB* distance is 4500m， upper slope is 1‰, *BC* distance is 9000m, lower slop is -1‰, *CD* distance is 4500m, slope is 1‰ upper, *DE* distance is 1600m. A train starts from *A* and stops E. The simulated train is SS_1 locomotive and its traction weight 3000 t, roll stocks are heavy axe load for freight, train conversion braking rate $\vartheta_h = 0.3$， line limited speed is 80 km/h, distance between switch and stop position is 1600m, switch limited velocity is 45 km/h, total running time is 25 min. The train can't pass station C in the time interval [16, 20].

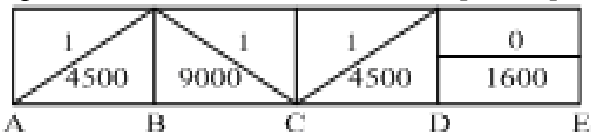

Fig.1 Simulation line diagram

On the basis of the length and slope of the line, train operation control model list in this simulation case is assumed to be comprised of two kinds of sequence lists.the first is : coast x_1 + traction x_2 + coast x_3 +brake x_4 and the second is coast x_1 + traction x_2 +coast x_3 + traction x_4 +coast x_5 +brake x_6. Both of the traction x_0=0.

Simulation Results

For two kinds of sequence list, this FA-based algorithm is implemented using two threads in Visual C++6.0 software development environment. The codes are running in main board frequency 1.86G, RAM1G hardware environment.

The computational results in Fig.2.show that the train should pass station C before 16 min adopting the first control sequence operation strategy. The solution is:

$X = (x1, x2, x3, x4) = (2812.31,15\ 285.68,173\ 19.89,1940\ 0.0)$

And total running distance is 1599.4m, total running time is 24.9956min, total energy consumption is 421.75kw.h.

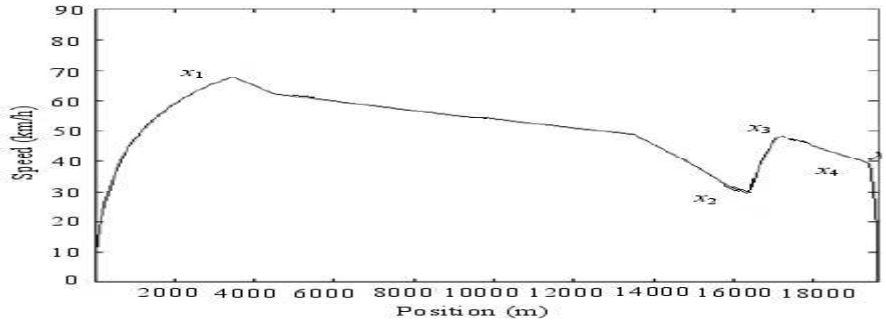

Fig.2 Train speed-position diagram

Comparison Analysis

What's more, in order to test different methods' result and their performance, computation results are compared in Table 1.

Table 1 Computation results comparison

Operation Strategy	Running time (min)	Energy Consumption (kW.h)	Train Passing Time in Station C (min)	Computation Time (min)
Time Saving	19.415	584.59	12.9687	_____
Target Speed	25.003	468.56	12.9687	_____
GA-based	24.9979	422.83	15.633	1520.68
FA-based	24.9956	421.75	15.628	1015.54

As can be seen in Table 1, energy consumption is much less for other 3 strategies compared to time-saving strategy. Also, running time of PSO-based algorithm is nearly a little more half of GA-based algorithm and it shows a better efficiency while keeping similar energy saving effect.

Conclusion

An energy saving control optimization model for train running operation under disturbed condition and it's solving algorithm are introduced in this paper. A new FA-based method is put forward to solve the model and computation results demonstrate that this new algorithm has a better performance compared to other methods, so it may be considered to be put into other train energy saving optimal control models.

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