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Research on operation control model of FAO system under compound-fault scene in urban rail transit

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ABSTRACT

This paper aims at the control decision of the compound-fault scene in urban rail transit Fully Automatic Operating (FAO) system. Under the compound-fault scene of vehicle fire and station fire occurring simultaneously, a bi-level optimization model is proposed for the operation control model of urban rail transit FAO system, and the validity of the model is verified by the simulation experiment. The simulation results show that the decision model can effectively find the optimal control points for the compound-fault occurrence of urban rail transit FAO system out, so as to carry out the active control and improve the operation efficiency of the urban rail transit system.

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Urban rail transit; FAO system; compound-fault scene; operation control; two-layer optimization model

1. Introduction

In recent years, with the prominence of traffic congestion, environmental pollution and energy consumption in large and medium-sized cities around the world, the people generally realize that the fundamental way to solve urban traffic problems lies in the development of urban public transport system with rail traffic as the backbone. Urban rail transit system relying on its large capacity, high efficiency, economy, environmental protection and comfort has gradually become the necessary infrastructure to realize the sustainable development policy of large and medium-sized cities at home and abroad. With the rapid development of urban rail transit, new demands have been put forward for the equipment system of urban rail transit construction and operation. Meanwhile, under the continuous promotion of modern communication technology and Internet of things technology to the development of rail traffic technology, the process of urbanization and the higher requirements for energy conservation and environmental protection are required. A Fully Automatic Operating System (FAO) that is stable, affordable and efficient would be needed urgently for the construction of global rail transport.

Presently, FAO is still in the initial stage of research in the world. Scholars both at home and abroad are actively solving the problems of each link of FAO system. Scholars have mainly focused the research of track traffic fault on identification, diagnosis, statistics and early warning technology for the research of the automatic driving track traffic system and fault treatment. In 2003, Curt A. Swenson from General Motors Co., Ltd. developed a remote monitoring and fault diagnosis system for locomotive based on commercial wireless communication network. The locomotive fault timely notified the maintenance base, shortened the maintenance time and improved the locomotive utilization and transport safety (Swenson, 2003). Wang (2014) set up a three-level comprehensive evaluation and early warning index system from early warning index with single factor, facilities and equipment integrated subsystem to line integrated system, and the threshold of early warning and grade for the three levels of rail transport facilities and equipment. Dooevoet, Huisman, Kroon, Schmidt, and Schöbel (2014) researched the train delay management problem from the macro level, mainly for the situation that the leading train is delayed on the transfer station, whether the following train is waiting for the leading delay train. Veelenturf, Kidd, Cacchiani, Kroon, and Toth (2016) studied the train operation adjustment under the whole line interval capacity and partial failure and gave a solution based on event-activity network. Bocharnikov, Tobias, Roberts, Hillmansen, and Goodman (2007) put forward a new method combining dynamic principle and driving strategy, setting appropriate fitness function by adjusting energy consumption and timetable limit so as to make the decision train use the most suitable method to pull or regenerative braking. Huang, Lou, Gong, and Edgar (2008) studied the application of fuzzy and predictive fuzzy theory in ATO system. By setting fuzzy rules and multiple fuzzy evaluation indexes, the control rule of fuzzy prediction system was con-

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structed. British researchers developed TCAS (Train Coasting Advisory System), which achieved the control on train operation under the condition that the train was not delayed. Domínguez, Fernández-Cardador, Cucala, Gonsalves, and Fernández (2014) applied the particle swarm optimization algorithm to the train autopilot system and designed the multi-objective optimization model of the train autopilot system. Finally, the control effect was verified from simulation and actual test. Zhu, Yu, Ning, and Tang (2014) elaborated the train control system (CBTC) and its subsystems in detail and the automatic train operation (ATO) function was combined with interlocking and central control operation to improve the control efficiency.

The research of this paper is based on urban rail transit FAO system to explore the operation control optimization under the compound-fault scene. The compound-fault scene is selected for vehicle fire and station fire at the same time, and the defaults of power are not lost when the fire vehicle is in the fire.

2. Selection and description of compound-fault scene

Scene hypothesis: Under the FAM mode, the train M_i fires and the station S_j fires at the same time.

Definition 2.1: T_a represents the abnormal operation time of a, which refers to the total time of system failure to failure recovery under FAO failure scene and $T_a > 0$.

Definition 2.2: F_a indicates the safety factor of a when the system fails and$0 \le F_a \le 1$. The greater is the value of F_a, and the higher security of the system. The corresponding safety factor is different for the different flow.

In order to analyse the impact of fire scene on T_a, according to the international standard ISO/TS 16733, the fire scenes in the rail transit system are divided into four grades as shown in Table 1.

Table 1. Classification of fire scene.

Fire grade	Fire description
I	Serious fire
II	Heavier fire
III	General fire
IV	Slight fire

3. FAO compound-fault scene operation control model based on bi-level optimization model

3.1. Establishment of the model

Given an urban rail transit network $G = (N, E)$,$N = \{1, 2, \ldots, n\}$ is a set of rail transit stations; E is a set of the stations connecting the sites; (r, s) is the O-D pair taking r as the starting point and s as the terminal; P_{rs} is a set of all sections between O–D pair and (r, s). At present, the rapid increase of potential traffic demand makes the road network overcrowding, which puts forward higher requirements for the safety of urban rail transit (Ataei, Hooshmand, & Samani, 2014; Corman, D'Ariano, Pacciarelli, & Pranzo, 2011; Dragicevic, Guerrero, & Vasquez, 2014; Gautam, Chu, & Soh, 2014; Moradzadeh, Boel, & Vandevelde, 2014; Yifeng, 2015; Yun, 2012). In this paper, we consider the optimal scheduling of vehicle operation in FAO system under the condition of compound-fault scenes occurring simultaneously in vehicle fires and station fires. Under the unified dispatching of TIAS (Train Information Automatic System), it is assumed that the system is fully aware of road conditions. Let R represent a set of all starting points; Srepresent a set of all endpoints; $T_a$represent the abnormal operation time of section$a$; C_a represent the maximum value of capacity of section$a$; u_{rs} is the minimum running time between O–D pair and (r, s); q^{rs} is the flow between O–D pair and (r, s) and the vector is $q = (\ldots, f^{rs}, \ldots)^T$, f^{rs} is the flow on path p between O-D pair and (r, s), and the vector is $f = (\ldots, f_p^{rs}, \ldots)^T$; x_a is the flow on section a and the vector is $x = (\ldots, x_a, \ldots)^T$. The travel time function of section a is $t_a(x_a)$, assuming that it is strictly monotonically increasing and continuously differentiable; if the path $p$between O–D pair and (r, s) passes section a, and $\delta_{ap}^{rs} = 1$; otherwise, $\delta_{ap}^{rs} = 0$. Therefore, we can build the following optimization model,

$$\begin{aligned} &\min_{x,q} \sum_{a \in E} \int_0^{x_a} t_a(\omega)d\omega + \sum_{r \in R} \sum_{s \in S} \int_0^{q^{rs}} T_{rs}(\omega)d\omega \\ &s.t. \sum_{p \in P_{rs}} f_p^{rs} = q_{rs} \\ &\quad \sum_{r \in R} \sum_{s \in S} \sum_{p \in P_{rs}} \delta_{ap}^{rs} f_p^{rs} = x_a \\ &\quad f_p^{rs} \ge 0 \end{aligned} \tag{1}$$

In the traffic flow control model (1), the direct solution of the equilibrium flow on each section does not directly reflect the real status of urban rail traffic flow, because in the compound-fault scene of the FAO system, an important factor that safety function of the section is also needed to be considered. Therefore, the urban rail transit control model in FAO compound-fault scene can be transformed into a bi-level programming model: the upper level is the maximum comprehensive security coefficient and the lower level is a traffic equilibrium model with traffic constraints. The bi-level optimization model is expressed as follows:

The upper level (maximum safety factor):

$$\max_{x,q} F(x,q) = \sum_{r\in R}\sum_{s\in S} F_{rs}(q^{rs}) \tag{2}$$

The lower level (traffic balance):

$$\min_{x} G(x,q) = \sum_{a\in E}\int_0^{x_a} t_a(\omega)d\omega + \sum_{r\in R}\sum_{s\in S}\int_0^{q_{rs}} T_{rs}(\omega)d\omega$$

$$\text{s.t.} \sum_{p\in P_{rs}} f_p^{rs} = q_{rs}$$

$$\sum_{r\in R}\sum_{s\in S}\sum_{p\in P_{rs}} \delta_{ap}^{rs} f_p^{rs} = x_a$$

$$f_p^{rs} \geq 0$$

Definition 3.1: Given the directional quantity q, x is the Pareto optimal solution of the lower level problem, and (x,q) is called the feasible solution of the above bi-level optimization problem.

Definition 3.2: If $(x*,q*)$ is the feasible solution of the above bi-level optimization problem and there is no feasible solution (x,q), which makes $F(x,q) < F(x*,q*)$, that $(x*,q*)$ is called the optimal solution of the bi-level optimization problem.

3.2. Solution of bi-level optimization problem

First, the particle swarm optimization algorithm is applied to solve the underlying optimization problem.

Step 1: For the fixed upper level decision vector q, initialize the lower level population P, the population size is N_P, initialize the lower level loop variables $t_P = 0$.

Step 2: Based on the lower level objective function and constraint condition, the corresponding uncontrolled class value L_P is allocated to each particle. For the examples with the same uncontrolled levels, the crowding degree distance of the example C_P is calculated based on the lower objective function $G(x,q)$;

Step 3: Store the particles with $L_P = 1$ in the total population P in the elite collection EL.

Step 4: Update the velocity and position of the lower layer particles:

$$v^t = \varpi v^t + c_1 r_1(pbest^t - y^t) + c_2 r_2(gbest^t - y^t),$$
$$y^{t+1} = y^t + v^{t+1}, \tag{3}$$

where ϖ represents the inertia weight; c_1, c_2 represent the self-learning factor and the social learning factor; r_1, r_2 represent the random numbers in the unit interval; *pbest* represents the individual historical optimal particle and *gbest* is the global optimal particle of the particle swarm.

Step 5: Redistribute the updated particles to uncontrolled level L_P and crowding degree C_P;

Step 6: The parent population FA_t and progeny population SO_t are merged into a new population NE_t. Based on the lower objective function $G(x,q)$ and constraint conditions, the uncontrolled rank values of the particles L_P in the parent population are redistributed, and the crowding degree C_P is calculated;

Step 7: Half of the particles are selected from population NE_t to form a new population NES_t, in which the particles are arranged in descending order of priority, and the particles are selected in turn until there are N_P particles in NES_t;

Step 8: Update the elite set EL;

Step 9: Let $t = t + 1$. Every T generation, we use KKT to deviate the measurement equation (the condition is proposed by Deb et al. in (Deb, 2016) for termination condition checking. If ε_k^* is greater than the preset accuracy, and then turn to step 4; otherwise, output EL. The KKT deviated metric equation is as follows:

$$\text{KKTPM } (x^k) = \begin{cases} \varepsilon_k^*, x \text{ is a feasible solution,} \\ 1 + \sum_{j=1}^{J} \langle g_j(x)\rangle, \text{ otherwise,} \end{cases} \tag{4}$$

where $\langle x\rangle = 0$, if $x \leq 0$; $\langle x\rangle = x$, if $x > 0$. The calculation of ε_k^* is as follows,

$$\min_{\varepsilon} \varepsilon_k$$

$$\text{s.t.} \left\| \sum_{r\in R}\sum_{s\in S} \nabla F_{rs}(q^{rs}) \right\|^2 \leq \varepsilon_k,$$

$$\sum_{a\in E}\int_0^{x_a} t_a(\omega)d\omega + \sum_{r\in R}\sum_{s\in S}\int_0^{q_{rs}} T_{rs}(\omega)d\omega - y_k \leq 0,$$

where y_k is the slack variable.

Based on the optimal solution of the lower level optimization problem, the optimal solution of the upper level optimization problem is solved. The basic process is to solve the lower level optimization problem by particle swarm optimization (PSO), and then feed the approximate optimal solution of the lower level optimization problem as the optimal response to the upper level, in order to solve the upper level optimization problem. Iterations are repeated to get the approximate optimal solution of the whole problem. The specific algorithms are as follows:

Step 1. Initialization of the upper population P_u, the size of the population is N_u, the maximum number of iterations is T_u. Initialize the upper cycle variable $t_u = 0$;

Step 2. For vector q, use algorithm 1 to solve $EL = \{x_0\}$, and then determine the candidate solution $q_0 = \arg\min_q \{F(x,q) : x \in EL\}$;

Step 3. Update the upper level decision variable q_0;
Step 3.1. Select $qbest$ and $gbest$:$qbest = q_0$ and $gbest = opt$;
Step 3.2. Speed update: $v_q = \vartheta v_q + c_1 r_1(qbest - q_0) + c_2 r_2(gbest - q_0)$ and location update: $q_{new} = q_0 + v_q$;
Step 3.3. For each q_{new}, utilize algorithm 1 to solve the lower level optimization problem and achieve x_{new};
Step 3.4. For each pair of $(q_{\text{new}}, x_{\text{new}})$, if $F(q_{\text{new}}, x_{\text{new}}) < F(q_0, x_0)$, use $(q_{\text{new}}, x_{\text{new}})$ to replace; otherwise, repeat Step 3;
Step 4. Let $t_u = t_u + 1$, if $t_u \le T_u$, and turn to step 3; otherwise, stop;

where ϑ is the inertia weight; c_1, c_2 is cognition coefficient and social coefficient; $r_1, r_2 \in$ random (0,1) is cognition coefficient and social coefficient.

4. Numerical simulation and result analysis

Considering a network of rail traffic with nine nodes, whose topology is shown in Figure 1, which contains an O–D point pair. There are a total of three paths$P_{OD1} = \{e_1, e_2, e_3\}$, $P_{OD2} = \{e_6, e_4, e_2, e_3\}$ and $P_{OD3} = \{e_6, e_5, e_3\}$ connecting to the O–D point pair. It is assumed that the free running time t_a^0 of each section is 1. The capacity data of each section are shown in Table 2.

Assuming that the travel time function is $t_a = t_a^0 \left(1 + 0.35\left(\frac{f_a}{C_a}\right)^{3.5}\right)$, the abnormal operation time function is $T_a = t_a^0 \left(1 + 0.4\left(\frac{|f_a - C_a|}{C_a}\right)^3\right)$, and the safety factor can be described as $F_a = \exp\left(-0.5\left(\frac{f_a}{C_a}\right)\right)$, among them, f_a is the traffic flow of section a. Supposing that there are 500 times' rail transit train passes through the O–D point pair; that is, there are 500 particles in the particle swarm algorithm, 5 particle groups in all. It is assumed that the termination time in algorithm 1 and algorithm 2 is 500. Repeat experiments 5 times, through algorithm 1 and algorithm 2, we can get the simulation results as shown in Figure 2. From Figure 2, we can see that the traffic flow on path P_{OD1} is the highest; path P_{OD2} is the second and path $P_{OD3}$is the least. In the five experiments, the traffic flow on each path tends to be the same with only a small gap. These small gaps are mainly caused by the random variables in the algorithm, which proves that the optimal solution of the bi-level optimization problem can be calculated by the designed particle swarm optimization (PSO) 1 and the algorithm 2. In the optimal solution, the flow of section $e_1, e_2, e_3, e_4, e_5, e_6$ is $136, 150, 500, 14, 350, 364$ in turn. Figure 3 and Figure 4 show the abnormal running time and safety factor of each section at equilibrium respectively. From Figures 2–4, it can be seen that section e_3 plays a very important role in

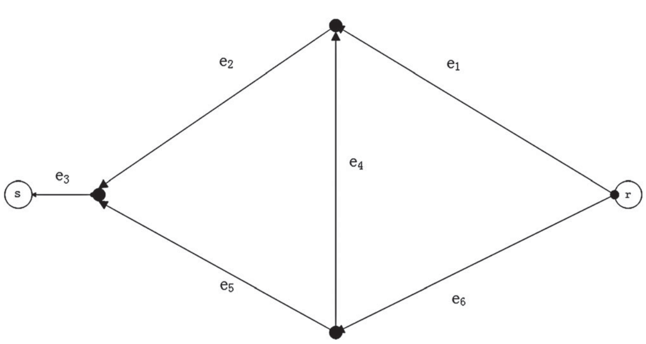

Figure 1. Network map of rail transit.

Table 2. Capacity of each section.

Section (a)	e_1	e_2	e_3	e_4	e_5	e_6
Capacity (c_a)	200	150	150	150	150	200

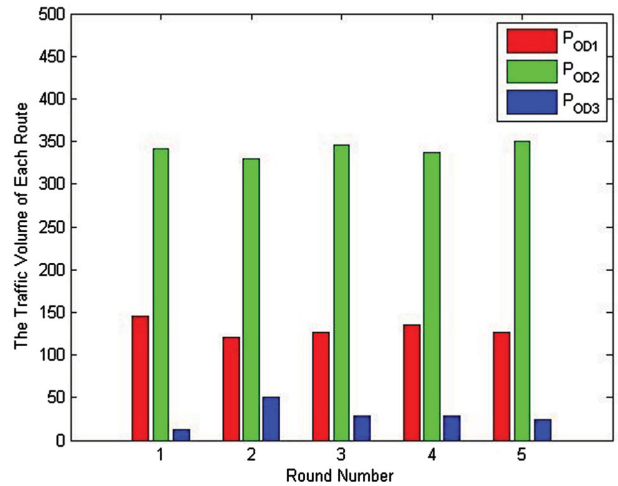

Figure 2. Traffic flow on the path.

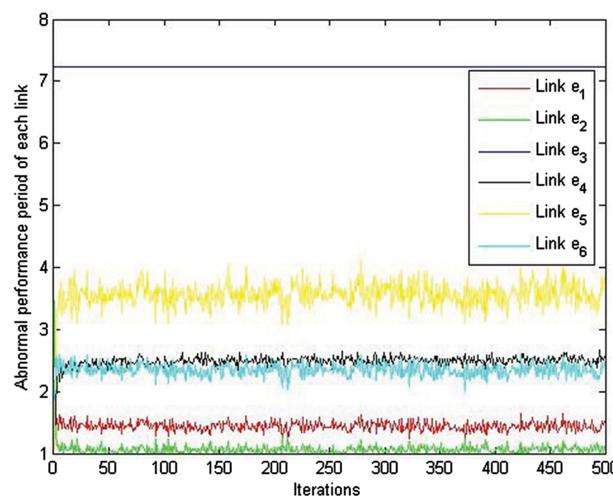

Figure 3. The abnormal running time of each section.

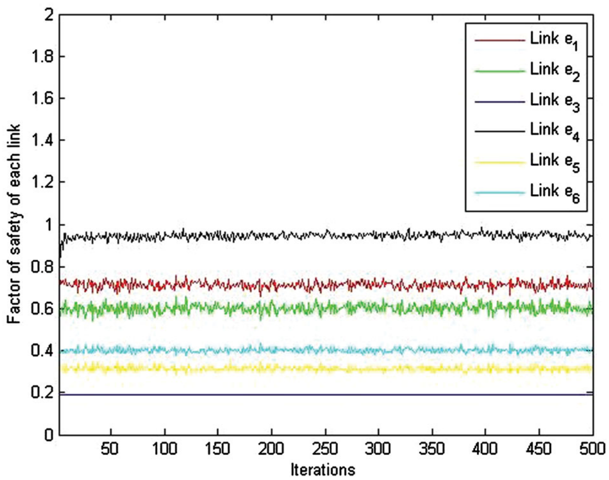

Figure 4. Safety factor on each section.

the track network. When the equilibrium is reached, the traffic flow is the maximum; the abnormal running time is the longest and the safety factor is the highest. The is because that section e_3 is the only way to the end s. Therefore, in order to improve the capacity of rail transit system and the efficiency of crisis management, we have to grasp the key point of section e_3. The best way is to build a split section on e_3 to reduce the pressure of the section, or to arrange more trains for traffic flow guidance. At the same time, attention should be paid to the sections e_1, e_2, e_5 with abnormal running time or high safety factor.

5. Conclusion

The paper aims at the control decision of urban rail transit FAO system under compound-fault scene, based on the whole urban rail transit network and under the specific compound-fault scene, an operation control model of FAO compound-fault scene on the basis of bi-level optimization model is proposed, and the validity of the model is verified through the simulation experiment. The simulation results show that the decision model can effectively find out the optimal control points for the compound-fault occurrence of urban rail transit FAO system, so as to carry out the active control and improve the operation efficiency of the urban rail transit system.

Disclosure statement

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