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

Zhongwei Hou\textsuperscript{a}, Feng Bao\textsuperscript{b}, Zixue Du\textsuperscript{a} and Zhen Yang\textsuperscript{a}

\textsuperscript{a}College of Traffic \& Transportation, Chongqing Jiaotong University, Chongqing, People’s Republic of China; \textsuperscript{b}Traffic Control Technology Co., Ltd, Beijing, People’s Republic of China

**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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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 train delay. Veelenturf, Kidd, Caccian, 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-
structured. British researchers developed TCAS (Train Coast-
ing Advisory System), which achieved the control on train
operation under the condition that the train was not
delayed. Domínguez, Fernández-Cardador, Cucala, Gon-
salves, 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 ver-
fied 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 oper-
ation (ATO) function was combined with interlocking and
central control operation to improve the control effi-
ciency.

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 \( 0 \leq F_a \leq 1 \). The greater is the value of
\( F_a \), and the higher security of the system. The correspond-
ing 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.

| Grade | 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 net-
work overcrowding, which puts forward higher require-
ments for the safety of urban rail transit (Ataei, Hoosh-
mand, & Samani, 2014; Corman, D’Ariano, Pacciarelli, &
Pranzo, 2011; Dragicevic, Guerrero, & Vasquez, 2014; Gau-
tam, Chu, & Soh, 2014; Moradzadeh, Boel, & Vandevelde,
2014; YiFeng, 2015; Yun, 2012). In this paper, we con-
sider 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 start-
ing points; \( S \) represent a set of all endpoints; \( T_r \) represent
the abnormal operation time of sections; \( C_p \) represent
the maximum value of capacity of sections; \( \tau_{rs} \) 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 \( f = (\ldots, f^{rs}, \ldots)^T \); \( x_{ap} \) is the flow
on section \( a \) and the vector is \( x = (\ldots, x_{ap}, \ldots)^T \). The travel
time function of section \( a \) is \( t_a(x_a) \), assuming that it is
strictly monotonically increasing and continuously differ-
etiable; 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,

\[
\begin{align*}
\min_{x_a} & \sum_{a \in E} \int_0^{x_a} t_a(\omega)d\omega + \sum_{r \in R} \sum_{s \in S} \int_0^{q^{rs}} T_{rs}(\omega)d\omega \\
\text{s.t.} & \sum_{p \in P_{rs}} f^{rs}_p = q^{rs} \\
& \sum_{r \in R} \sum_{s \in S} \sum_{p \in P_{rs}} \delta_{ap}^{rs} f^{rs}_p = x_a \\
& f^{rs}_p \geq 0 
\end{align*}
\]

In the traffic flow control model (1), the direct solu-
tion 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 coef-
ficient 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):

$$\max_{x,q} F(x, q) = \sum_{r \in R} \sum_{s \in S} F_{rs}(q^s)$$  \hspace{1cm} (2)

The lower level (traffic balance):

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

s.t.

$$\sum_{p \in P_{rs}} f_{p} = q_{rs}$$

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

$$f_{p} \geq 0$$

**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 unconstrained 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:

$$v^t = \omega v^t + c_1 r_1 (p_{best}^t - y^t) + c_2 r_2 (gbest^t - y^t),$$

$$y^{t+1} = y^t + v^{t+1},$$  \hspace{1cm} (3)

where $\omega$ 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; $p_{best}$ 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 $\epsilon^*_k$ is greater than the preset accuracy, and then turn to step 4; otherwise, output $EL$. The KKT deviated metric equation is as follows:

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

where $(x) = 0$ if $x \leq 0$; $(x) = x$, if $x > 0$. The calculation of $\epsilon^*_k$ is as follows,

$$\min_{\epsilon} \epsilon_k$$

s.t.

$$\sum_{r \in R} \sum_{s \in S} \nabla F_{rs}(q^s)^2 \leq \epsilon_k,$$

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

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 $q_0 \in q$.
Step 3. Update the upper level decision variable \( q_0 \);
Step 3.1. Select \( q_{\text{best}} \) and \( g_{\text{best}} \):
\( q_{\text{best}} = q_0 \) and \( g_{\text{best}} = \text{opt} \);
Step 3.2. Speed update: \( v_q = \vartheta v_q + c_1 r_1(q_{\text{best}} - q_0) + c_2 r_2(g_{\text{best}} - q_0) \) and location update: \( q_{\text{new}} = q_0 + v_q \);
Step 3.3. For each \( q_{\text{new}} \), utilize algorithm 1 to solve the lower level optimization problem and achieve \( x_{\text{new}} \);
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 \( t_u \leq T_u \), and turn to step 3; otherwise, stop;

where \( \vartheta \) is the inertia weight; \( c_1, c_2 \) is cognition coefficient and social coefficient; \( r_1, r_2 \in \text{random (0,1)} \) 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 \( P_{0D1} = \{e_1, e_2, e_3\} \), \( P_{0D2} = \{e_6, e_4, e_2, e_3\} \) and \( P_{0D3} = \{e_6, e_5, e_3\} \) connecting to the O–D point pair. It is assumed that the free running time \( t_0^0 \) of each section is 1. The capacity data of each section are shown in Table 2.

Assuming that the travel time function is \( t_a = t_0^0 \left( 1 + 0.35 \left( \frac{f_a}{c_a} \right)^{3.5} \right) \), the abnormal operation time function is \( T_a = t_0^0 \left( 1 + 0.4 \left( \frac{|f_a - c_a|}{c_a} \right)^{3} \right) \), 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 \( P_{0D1} \) is the highest; path \( P_{0D2} \) is the second and path \( P_{0D3} \) 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, 150, 150, 150, 200 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...
the key point of section and the efficiency of crisis management, we have to grasp first, in order to improve the capacity of rail transit system time, attention should be paid to the sections 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. 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.

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