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Research paper

Research on emergency bus shuttle dispatch under sudden interruption of urban rail transit

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Abstract: Rail transit systems, fundamental to urban mobility, frequently encounter disruptions necessitating prompt and effective emergency responses, particularly for connecting bus services that transport passengers to affected rail lines. This research paper explores emergency dispatch methods for abnormal connecting buses in urban rail transit, concentrating on enhancing the responsiveness and efficiency of dispatch protocols during non-standard operational scenarios. By delineating the emergency shuttle service process and identifying key factors, a shuttle bus emergency dispatch model was developed for both single-line and multi-line emergency scenarios, considering passenger travel behavior and vehicle operation modes. The decision variables included the stopping plan, dispatch quantity, and departure frequency, with the objective of minimizing total passenger travel time. Constraints related to resources, time, demand, safety, and physical limitations were incorporated. Given the integer nature of the decision variables concerning the number of vehicles dispatched and the stopping plan, a solution process was designed using a discrete particle swarm optimization (DPSO) algorithm, and the model was subsequently solved.

Keywords: rail transit, emergency connection, emergency dispatch model, discrete particle swarm optimization

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1. Introduction

In the sphere of public transportation, rail transit is a fundamental pillar of urban mobility, enabling the daily commutes of millions and supporting economic sustainability [1,2]. The efficiency and reliability of urban rail systems are crucial, yet ensuring their safety is a continuous challenge. Rail traffic safety presents a multifaceted issue that requires meticulous coordination across various components of the rail network [3]. The infrastructure, which includes tracks, signaling systems, and rolling stock, must adhere to stringent safety standards to prevent accidents and maintain seamless operations [4]. Technological advancements have introduced sophisticated safety measures such as automated train control systems [5], real-time monitoring [6], and predictive maintenance [7]. Nevertheless, the rail industry remains susceptible to unexpected incidents, including equipment failures, human errors, natural disasters, and deliberate sabotage [8]. These incidents can trigger emergencies that demand swift and effective responses to mitigate risks and reestablish normal operations.

Central to the mitigation of rail traffic emergencies is the emergency dispatch system, which acts as the nerve center for coordinating incident responses [9]. Emergency dispatching in rai 1l transit is distinguished by its complexity and the necessity for rapid, decisive action. Dispatch protocols are meticulously designed to minimize response times and ensure the optimal allocation of resources. This process demands seamless communication and collaboration among various stakeholders, including rail operators, emergency services, and government agencies. Dispatchers are pivotal in this framework, tasked with assessing the situation, prioritizing actions, and directing response efforts [10]. The effectiveness of these dispatch systems is critical in non-normal situations, where the stakes are elevated, and the margin for error is exceedingly narrow.

One of the primary challenges in emergency dispatching for rail transit lies in the inherent unpredictability and variability of incidents [11]. Each emergency brings a distinct set of circumstances that necessitate a customized response. For example, a derailment in an urban environment presents different challenges than one in a rural area. Factors such as the severity of the incident, the potential for secondary hazards, and site accessibility all shape the dispatch strategy [12]. Therefore, emergency dispatch protocols must be intrinsically flexible a 1nd adaptive, incorporating past experiences and leveraging the latest technological advancements to enhance their effectiveness.

In recent years, substantial progress has been achieved in integrating advanced technologies into emergency dispatch systems. The emergence of artificial intelligence (AI) and machine learning has added new dimensions to emergency management by enabling more accurate predictions, real-time data analysis, and enhanced decision-making [13]. These technologies enhance the capabilities of human dispatchers, providing actionable insights and optimizing resource allocation. Additionally, the incorporation of geographic information systems (GIS) [14] and advanced communication tools improves situational awareness and facilitates coordinated responses across multiple agencies [15]. These technological advancements show great potential for transforming emergency dispatching in rail transit, making it more efficient and effective.

This research paper aims to develop an emergency dispatch model for urban rail transit's abnormal connecting buses. First, it comprehensively categorizes and summarizes scenarios involving non-normal events in rail transit, analyzing the key factors that impact the effectiveness of connections. Next, a shuttle bus emergency dispatch model is formulated with decision variables including the stopping plan, dispatch quantity, and departure interval, with the objective of minimizing total passenger travel time. The model incorporates multiple constraints such as vehicle resources, shuttle demand, shuttle time, full load rate, and physical limitations. Finally, a discrete particle swarm optimization method is designed to solve the model, tailored to its specific characteristics.

2. Key factors for urban emergency connection

The emergency connection response process should encompass three stages: evaluation, handling, and response. This study delineates these stages into the following three steps, corresponding to the connection service process illustrated in Fig. 1.

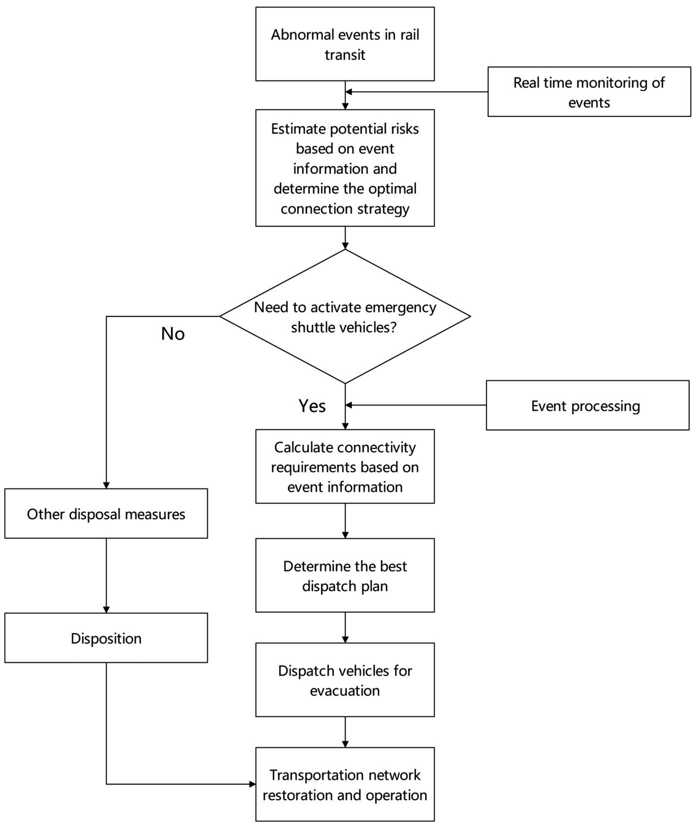

Fig. 1. Flow chat of abnormal emergency connection service

3. Problem description

Assuming the rail transit network experiences abnormal events causing delays or interruptions on the i-th routes and resulting in service disruptions at the j-th stations, it becomes necessary to utilize the remaining capacity of nearby buses or deploy shuttle buses from appropriate dispatch points to evacuate passengers. These shuttles will bridge the affected stations, operating in a loop along the original rail transit line to restore network connectivity. At this juncture, it is crucial to reasonably adjust the number of dispatched buses, operating modes, and departure intervals based on the impact of the abnormal conditions, passenger flow demand at each station, traffic conditions, and vehicle operation times, to swiftly evacuate passengers.

If the connecting buses serving the disrupted stations come from multiple dispatch points and operate in various modes, these different dispatch points and operating modes are referred to as routes for ease of description. Considering the urgency of emergency transportation, the objective is to minimize the total travel time for all passengers. Let the duration of the abnormal state be T_{inte}; the OD passenger flow between disrupted sites $inte_i$ and $inte_j$ be Q_{ij}; the number of passengers present at station $inte_j$ at the moment of interruption be Q'_j; the daily passenger flow demand of the up and down sections at the turnaround station of line q_i^{up} and q_i^{down}; the travel time for connecting buses from dispatch point $disp_i$ to interruption point $inte_j$ be t_{ij}; the travel time from interruption point $inte_i$ to the next stop of the connecting bus be t'_i; and the stopping time of the connecting bus at interruption point $inte_i$ be t_i^{stop}. The available vehicle resources at dispatch point $disp_i$ are X_i, and the alternative conditions for each disrupted station are known.

Under these conditions, the total travel time $T$of passengers can be calculated as a function of the number of vehicles x_{ij}, departure frequency f_{ij}, and stopping plan σ_{ij} dispatched by dispatch point $disp_i$ on the j-th route, i.e., $T_{\text{total}} = F(x, f, \sigma)$. Additionally, by considering various constraints such as vehicle resources, connection requirements, and safety requirements, the decision variables x_{ij}, f_{ij}, and σ_{ij} of the model are ultimately determined to optimize the objective function and facilitate rapid passenger evacuation.

4. Determination of key parameters of the model

4.1. Emergency connection requirements

As a critical parameter of the model, the connection demand at each disrupted station directly influences the final dispatching plan and operational route. Therefore, it is essential to accurately calculate the emergency connection demand. Currently, there are two primary methods to characterize emergency connection needs. The first method relies on historical data to estimate the impact of events on connection requirements. The second method involves obtaining passenger flow allocation through deduction or simulation models, combined with passenger selection behavior. Given that the essence of different demand modes is a result of passenger choices, this study employs an unconventional passenger travel mode selection model based on the cumulative prospect theory. This model is combined with the number of affected passenger flows identified in previous studies to calculate the emergency shuttle demand. The shuttle demand for the unconventional station $inte_i$ is formulated in Eq. (4.1) and Eq. (4.2).

$$dema_i = \sum_j dema_{ij} + Q'_i \tag{4.1}$$

$$dema_{ij} = \begin{cases} P_{ij}^{\mathrm{cbus}} \times T_{\mathrm{inte}} \times Q_{ij}, & inte_i \in \mathrm{MS} \\ P_{ij}^{\mathrm{cbus}} \times \left[T_{\mathrm{inte}} \times \left(Q_{ij} + \max\left\{q_i^{\mathrm{up}}, q_i^{\mathrm{down}}\right\}\right)\right], & inte_i \in \mathrm{TBS} \end{cases} \tag{4.2}$$

where: $dema_{ij}$ represents the connection requirements between the abnormal site $inte_i$ and the abnormal site $inte_j$; $dema_i$ represents the total connection demand of the abnormal site $inte_j$; P_{ij}^{cbus} represents the proportion of passengers choosing shuttle buses when traveling from non-normal station $inte_i$ to non-normal station intej; Q'_i represents the number of passengers present in the system at the moment of interruption at the abnormal station $inte_i$; Q_{ij} represents the OD affected passenger flow between the non-normal site $inte_i$ and the abnormal site $inte_j$; q_i^{up} and q_i^{down} respectively represent the daily up and down section passenger flow of abnormal stations; T_{inte} is the duration of an abnormal event; MS and TBS respectively represent the collection of intermediate stations and turnaround stations in rail transit.

4.2. Total travel time of passengers

The total travel time for passengers during abnormal events in rail transit encompasses three main components: the retention time within the rail transit system, the waiting time for various modes of transportation, and the travel time on the shuttle bus. This paper focuses exclusively on the total travel time for passengers utilizing the shuttle bus mode, with other modes calculable by analogy.

1. Detention Time: Passengers affected by abnormal events include those within the rail transit system at the moment of interruption and those outside the system before the interruption, unable to reach their destination as originally planned. Assuming the passenger arrival rate at the disrupted station $inte_i$ remains constant, and some passengers consider changing their original plans, let the probability of this change be P_i^{change}. At this juncture, the total number of affected passengers, the cumulative number of departing passengers, and the cumulative number of stranded passengers at the disrupted station $inte_i$ can be represented by Eqs. (4.3)–(4.5). The relationship between the number of passengers and time is illustrated in Fig. 2.

$$Q_i^{\mathrm{total}} = Q_i \times T_{\mathrm{inte}} + Q'_i \tag{4.3}$$

$$Q_i^{\mathrm{leave}} = P_i^{\mathrm{change}} \times Q_i^{\mathrm{total}} = P_i^{\mathrm{change}} \times Q'_i \times T_{\mathrm{inte}} + P_i^{\mathrm{change}} \times Q'_i \tag{4.4}$$

$$Q_i^{\mathrm{stay}} = Q_i^{\mathrm{total}} - Q_i^{\mathrm{leave}} \tag{4.5}$$

where, Q_i^{total}, Q_i^{leave}, and Q_i^{stay} represent the total number of affected passengers, the cumulative number of departing passengers, and the cumulative number of stranded passengers at the abnormal station $inte_i$, respectively. Q_i and Q'_i denote the daily passenger flow at the abnormal station $inte_i$ and the number of passengers present in the system at the moment of interruption,

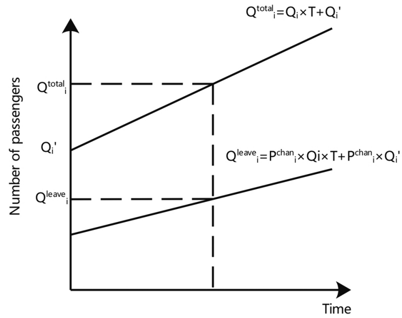

Fig. 2. Cumulative number of stranded passengers

respectively. The meanings of other parameters remain consistent with previous definitions. The shaded area in the figure represents the total residence time of passengers at the station, as illustrated in Eq. (4.6).

The total detention time for all passengers is the sum of the detention times at all affected stations, as shown in Eq. (4.7). The p_i^{change} is influenced by the alternative transportation conditions and the strength of the emergency connection at the station. Consequently, the delay time is partially dependent on the dispatch plan for the connecting buses.

$$T_i^{\text{stay}} = \frac{\left(P_i^{\text{change}} \times Q_i' + Q_i^{\text{stay}}\right) \times T_{\text{inte}}}{2} \tag{4.6}$$

$$= Q'_i \times T_{\text{inte}} \times \left(1 - P_i^{\text{change}}\right) + \frac{Q'_i \times T_{\text{inte}} \times \left(1 - P_i^{\text{change}}\right)}{2}$$

$$T^{\text{stay}} = \sum_i T_i^{\text{stay}} \tag{4.7}$$

where: T_i^{stay} is the total passenger stay time at station $inte_i$; T^{stay} refers to the total passenger retention time at all stations.

2. Waiting Time: This study primarily addresses the waiting time for shuttle buses, while waiting times for other transportation methods can be determined based on respective departure intervals, vehicle counts, and so on. Due to the necessary response time for emergency shuttle services, it is not feasible for the shuttle bus to arrive at the station and commence services immediately at the moment of an incident. Consequently, passengers already inside the station before the incident will experience a longer average waiting time than those arriving after the emergency shuttle service is fully operational. Assuming the number of passengers stranded at abnormal station $inte_i$ before the interruption is Q_i', the time taken for a shuttle bus from dispatch point $disp_j$ to reach abnormal station $inte_i$ is t_{ji}, and the corresponding departure frequency is f_{ji}, Q_i' requires n_i vehicles to be completely dispersed. At this point, the total waiting time for the first batch of evacuated passengers is $(Q_i' \times t_{ji})/n_i$, and the total waiting time for the second batch of evacuated passengers is $Q_i' \times (t_{ji} + 1/f_{ji})/n_i)$. If an abnormal station receives vehicle support from multiple dispatch points, from the passengers' perspective

at that station, it equates to a combined departure frequency of $\sum_j f_{ji}$. Hence, the total waiting time for all stranded passengers at abnormal station $inte_i$ before the interruption is illustrated in Eq. (4.8). After the emergency shuttle service is fully activated, due to the shuttle bus's circular operation, the waiting time for passengers depends only on the number of circulating vehicles passing through the station. More circulating vehicles result in shorter passenger waiting times and a higher proportion of passengers choosing this method. Assuming the number of shuttle bus routes serving station $inte_i$ is j, with corresponding vehicle counts of x_{ij}, the total waiting time for passengers at station $inte_i$ after the emergency transfer activation is shown in Eq. (4.9).

$$T_i^{\text{wait1}} = \frac{P_i^{\text{cbus}} \times Q_i' \times \left(n_j \times t_{ji} + \sum_{i=1}^{n_j - 1} i / \sum_j f_{ji} \right)}{n_j} \tag{4.8}$$

$$T_i^{\text{wait2}} = Q_i' \times T_{\text{inte}} \times P_i^{\text{cbus}} \times t_j / \sum_j x_{ij} \tag{4.9}$$

where, T_i^{wait1} represents the total waiting time of all stranded passengers within station $inte_i$ before the start of the transfer; T_i^{wait2} represents the total waiting time of passengers arriving at station $inte_i$ after the emergency shuttle is activated; The meanings of other parameters are the same as above.

In summary, the total waiting time of all passengers at station $inte_i$ is shown in Eq. (4.10), and the waiting time of all passengers is the sum of the waiting times of all passengers at the station, as shown in Eq. (4.11):

$$T_i^{\text{wait}} = T_i^{\text{wait1}} + T_i^{\text{wait2}} = F(x_{ij}, f_{ji}) \tag{4.10}$$

$$T^{\text{wait}} = \sum_i T_i^{\text{wait}} \tag{4.11}$$

where, T_i^{wait1} represents the total waiting time of all passengers at station $inte_i$; Wait represents the total waiting time of all passengers at all stations; The meanings of other parameters are the same as above.

3. In car time: Taking shuttle buses as an example, in car time includes both vehicle travel time and stop time, so passenger in car time is related to the number of stops and vehicle travel time. Assuming that the stopping time of the vehicle at the abnormal station $inte_i$ is tistop; The travel time from station $inte_i$ to the next stop is t_i', the passenger flow from station $inte_i$ to station $inte_j$ is Q_{ij}, the set of stop points for connecting route j is K_{ij}, and the stop discrimination parameter for connecting bus is σ_{ij}. When $\sigma_{ij} = 1$, it indicates that the connecting line j stops at station $inte_i$ and provides connecting services, otherwise it does not stop, as shown in Eq. (4.12):

$$\sigma_{ij} = \begin{cases} 0, & inte_i \notin K_{ij} \\ 1, & inte_i \in K_{ij} \end{cases} \tag{4.12}$$

At this time, the total stopping time of all passengers from station $inte_i$ to station $inte_j$ and the vehicle travel time are shown in Eqs. (4.13) and (4.14), respectively, and the total on board time is shown in Eq. (4.15). By performing the same treatment on all stations and summing them up, the total time of all passengers in the abnormal state can be obtained as shown in Eq. (4.16).

$$T_{ij}^{\text{stop}} = Q_{ij} \times T_{\text{inte}} \times P_i^{\text{cbus}} \times \sum_i (t_i^{\text{stop}} \times \sigma_{ij}) \tag{4.13}$$

$$T_{ij}^{\text{move}} = Q_{ij} \times T_{\text{inte}} \times P_i^{\text{cbus}} \times \sum_i^{j-1} t'_i \tag{4.14}$$

$$T_{ij}^{\text{trav}} = T_{ij}^{\text{stop}} + T_{ij}^{\text{stop}} = G(\sigma_{ij}) \tag{4.15}$$

$$T^{\text{trav}} = \sum_i \sum_j T_{ij}^{\text{trav}} \tag{4.16}$$

where, T_{ij}^{stop} represents the total stopping time of all passengers between stations i and j; T_{ij}^{move} represents the total travel time of all passengers between stations $inte_i$ and intej; T_{ij}^{trav} represents the total time all passengers are on the train between station $inte_i$ and intej; T^{trav} represents the total on time of all passengers at all stations; The meanings of other parameters are the same as above.

In summary, the total travel time T^{cbus} of passengers under the shuttle bus mode is the sum of the above three parts of time.

5. Emergency dispatch model for connecting public transportation

5.1. Single line abnormal events

In response to abnormal events on a single track, a nonlinear programming model is established with stopping strategy, dispatching quantity, and departure frequency as decision variables, and the goal of minimizing the total travel time of connecting passengers. Vehicle resources, connecting demand, connecting time, and safety constraints are considered to establish the following:

(1) Objective function

Based on the quantification method of passenger travel time in section 4.2, it can be seen that the total travel time of all passengers who travel from the abnormal station $inte_i$ to the abnormal station $inte_j$ and choose to connect to the bus is shown in Eqs. (5.1)–(5.3):

$$T_{ij}^{\text{cbus}} = T_{ij}^{\text{trav}} + T_i^{\text{wait}} = T(x_{ij}, f_{ji}, \sigma_{ji}) \tag{5.1}$$

$$\begin{aligned} T_{ij}^{\text{trav}} &= T_{ij}^{\text{stop}} + T_{ij}^{\text{move}} \\ &= Q_{ij} \times T_{\text{inte}} \times P_i^{\text{cbus}} \times \sum_i (t_i^{\text{stop}} \times \sigma_{ij}) + Q_{ij} \times T_{\text{inte}} \times P_i^{\text{cbus}} \times \sum_i^{j-1} t'_i \end{aligned} \tag{5.2}$$

$$T_i^{\text{wait}} = T_i^{\text{wait1}} + T_i^{\text{wait2}} \tag{5.3}$$

Sum up the travel time of all passengers between stations, calculate the total travel time of all passengers taking connecting buses under abnormal events as shown in Eq. (5.4), and set it as the model objective function.

$$T^{\text{cbus}} = \sum_i \sum_j T_{ij}^{\text{cbus}} \tag{5.4}$$

where: T_{ij}^{cbus} represents the total travel time of all passengers who travel from the abnormal station $inte_i$ to the abnormal station $inte_j$ and choose to connect to the bus; T^{cbus} represents the total travel time of all passengers who choose to take public transportation between each station.

(2) Constraints 1. Resource constraint: Due to limited vehicle resources, the sum of the number of vehicles dispatched by any dispatching point to each route must not exceed the available number of vehicles at that dispatching point, as shown in Eq. (5.5):

$$\sum_j x_{ij} < X_i, \quad \forall i \in S \tag{5.5}$$

where: x_{ij} represents the number of vehicles dispatched from dispatch point $disp_i$ to route j; X_i represents the available vehicle resources of the dispatch point dispi; S is the collection of connecting bus dispatch points.

2. Demand constraint: Ensure that the transportation capacity provided by the connecting bus meets the connecting demand, and ensure that all stranded passengers at abnormal stations along the way can be effectively relieved, as shown in Eq. (5.6), where the connecting capacity is characterized by introducing the maximum number of connecting bus cycles.

$$C^{\text{extra}} \times \delta_B \times \sum_j \left(x_{ij} \times \sigma_{ij} \times N_j \right) \geq dema_i, \quad \forall i \in D \tag{5.6}$$

where: C^{extra} is the rated passenger capacity of the connecting bus; δ_B is the maximum load capacity; σ_{ij} is the parameter for stopping at the station; N_j is the number of vehicle cycles on line j; $dema_i$ is the connection demand for site $inte_i$; D is a collection of abnormal sites.

3. Time constraint: If rail transit resumes operation, emergency connections will lose their necessity. Therefore, it is required to evacuate stranded passengers within a limited time, which is reflected in demand constraints and also in the total time that any vehicle takes from the dispatch point to the end of the circular shuttle task, not exceeding the duration of the abnormal state, as shown in Eq. (5.7):

$$t_{ij} + N_j \times \left[\sum_i \left(t_i^{\text{stop}} \times \sigma_{ij} \right) + \sum_i t_i' \right] \leq T_{\text{inte}}, \quad \forall i \in S, \forall j \tag{5.7}$$

where, t_{ij} represents the time for connecting buses from dispatch point $disp_i$ to route j; t_i^{stop} represents the stopping time of the connecting bus at the abnormal stop $inte_i$; t_i' represents the running time of the connecting bus from station $inte_i$ to the next station.

4. Continuous constraint: To ensure the continuity and stability of the connection, it is required that the first departing vehicle can return to the interruption point and connect

again when the last connecting bus departs, in order to avoid service gaps caused by uneven distribution of vehicles. In addition, it should also meet the maximum and minimum departure interval restrictions in the "Urban Public Bus and Trolley Passenger Service" standard:

$$\frac{\sum_i x_{ij}}{\sum_i f_{ij}} \geq \sum_i t'_i, \quad f_{\min} \leq f \leq f_{\max}, \forall j \tag{5.8}$$

where: f_{ij} represents the departure frequency of vehicles dispatched from dispatch point $disp_i$ to route j; $f_{\min}$ and $f_{\max}$ represent the maximum/minimum departure frequency limits, respectively; The meanings of other parameters are the same as above.

5. Safety constraints: Considering the safety of emergency connections, it is required that the actual full load capacity of all vehicles on all lines shall not exceed the maximum full load capacity limit:

$$\delta_{Bj} \leq \delta_B, \quad \forall j \tag{5.9}$$

6. Physical constraint: In the actual connection process, the number of dispatched vehicles can only be a positive integer; There are only two types of service states for all vehicles at any abnormal station: stationary and non-stationary, as shown in Eq. (5.10):

$$x_{ij} \in N^+, \quad \sigma_{ij} \in \{0, 1\} \tag{5.10}$$

5.2. Multi-line abnormal events

Referring to the modeling approach of single line events, a nonlinear programming model is established with the decision variables of stopping strategy, dispatching quantity, and departure frequency, and the goal of minimizing the total travel time of connecting passengers. The model takes into account vehicle resources, connecting demand, connecting time, and safety constraints, as shown in Eqs. (5.11) and (5.12).

$$\min T^{\text{cbus}} = \sum_i \sum_j T_{ij}^{\text{cbus}} + T^{\text{chan}} \tag{5.11}$$

$$\begin{cases} \sum_j x_{ij} \leq X_i, & \forall i \in S \\ C^{\text{extra}} \times \delta_B \times \sum_j (x_{ij} \times \sigma_{ij} \times N_j) \geq dema_i, & \forall i \in D \\ t_{ij} + N_j \times \left[\sum_i \left(t_i^{\text{stop}} \times \sigma_{ij} \right) + \sum_i t'_i \right] \leq T_{\text{inte}}, & \forall i \in S, \forall j \\ \frac{\sum_i x_{ij}}{\sum_i f_{ij}} \geq \sum_i t'_i, & f_{\min} \leq f \leq f_{\max}, \forall j \\ \delta_{Bj} \leq \delta_B, & \forall j \\ x_{ij} \in N^+, & \sigma_{ij} \in \{0, 1\} \end{cases} \tag{5.12}$$

Considering the difficulty of connecting all stations by connecting buses during abnormal events on multiple lines. Therefore, for passengers who need to travel across different routes, additional transfer time for connecting buses should be added. If the waiting time of passengers for new line vehicles after transfer is not considered, this part of the time is only related to the number of passengers who need to travel across the line. At this point, the total transfer time of all passengers who need to travel across the line is shown in formula (5.13):

$$T^{\text{chan}} = \sum_i \sum_j \left(Q_{ij} \times \omega_{ij} \times T_{\text{inte}} \times P_i^{\text{cbus}}\right) \times t^{\text{chan}} \tag{5.13}$$

where T^{chan} represents the total transfer time of all passengers; t^{chan} represents the transfer time; ω_{ij} is a variable from 0 to 1, take 0 when station $inte_i$ and station $inte_j$ belong to the same line, otherwise take 1.

The meanings of other symbols are the same as above. In summary, the practical significance of the above shuttle bus scheduling model is to adjust the number of dispatched buses, stop plans, and departure intervals, and use existing vehicle resources to quickly complete the task of relieving all passengers within a limited time.

5.3. Sensitivity analysis

In theory, reasonable shuttle bus scheduling can effectively alleviate stranded passengers, but due to multiple constraints, it cannot infinitely reduce passenger travel time. From the above model, it can be seen that the adjustable parameters that constrain the results of the model include the maximum load capacity limit of the vehicle σ and the available vehicle resource limit X. The more passengers a sin gle vehicle can accommodate or the stronger the emergency transfer, the more obvious the effect of relieving stranded passengers. Therefore, it is allowed to adjust δ and X within a certain range, observe the sensitivity of the model regarding the above parameters, and determine the extent of improvement in the connection effect. However, considering the safety of emergency connections, the maximum load capacity of the vehicle should still be within the specified range. Meanwhile, based on the reality, the available vehicle resources cannot be infinitely increased.

6. Solving algorithm

Due to the information exchange mechanism inherent in Particle Swarm Optimization (PSO), the likelihood of all particles concurrently converging on the same local optimum is exceedingly low. This characteristic effectively mitigates the risk of premature convergence, which is a common drawback in optimization problems. Consequently, PSO demonstrates superior performance in solving vehicle scheduling problems compared to genetic algorithms. Given that the number of vehicles dispatched in the model's decision variables must be a positive integer, the Discrete Particle Swarm Optimization Algorithm (DPSO) was selected as the most suitable method for addressing this problem [16].

The classical PSO algorithm finds the optimal solution by emulating the collaborative behavior of bird flocks. However, in the iterative process, the initial particle positions, search step sizes, and iteration directions are all treated as continuous values, whereas in vehicle scheduling problems, these parameter values need to be discrete. To accommodate this, the discrete particle swarm optimization (DPSO) algorithm was utilized. DPSO retains the fundamental principles and iterative methods of classical PSO but modifies the approach by using a sigmoid function to map the particle velocities of each iteration to a range between 0 and 1, thereby enabling binary classification. This ensures that each iteration value is either 0 or 1, achieving the desired discretization effect. The expression for the sigmoid function is provided in Eq. (6.1).

$$S(x_i) = \frac{1}{1 + \exp(-x_i)} \tag{6.1}$$

Based on the model's characteristics outlined in this study, a positive integer constraint is applied to the number of trains dispatched, and a binary (0–1) constraint is applied to the stopping plan. All potential stopping plans are thoroughly examined, with each distinct plan treated as a new route. Consequently, the decision-making process is streamlined to determining the number of dispatched trains and the departure frequency for each route, while integrating various decision variables into a single vector. This approach significantly reduces the model's complexity. The solution method proceeds as follows.

Each element in the particle position vector corresponds to a model decision variable in each iteration. Utilizing the DPSO iteration method, the individual and global positions with the best fitness are calculated and recorded during each iteration. The final iteration result is considered the ultimate solution of the model. Additionally, while satisfying positive integer constraints, it is crucial to ensure that each dimension in the vector adheres to boundary constraints, such as maximum and minimum dispatching numbers and departure frequency limits, i.e., $X_i \subset [X_{\min}, X_{\max}]$. The individual and global position vectors are represented in Eq. (6.2).

$$\begin{cases} X_i^k = \left(x_{i1}^k, x_{i2}^k, \ldots, x_{ij}^k, f_{i1}^k, f_{i2}^k, \ldots, f_{ij}^k\right) \\ Pbest\, x_i^k = \min^k\{X_i^k\} \\ Gbest\, x_i^k = \min_i\{Pbest\, x_i^k\} \end{cases} \tag{6.2}$$

where, X_i^k is the search vector of particle i in the k-th round; The components x_{ij}^k and f_{ij}^k respectively represent the number of vehicles dispatched from point i to route j in the k-th round and the departure frequency; $Gbest\, x^k$ is the optimal solution of the model.

When solving optimization problems, it is generally required that the fitness function is non-negative. For maximization problems, the objective function itself can be used directly. For minimization problems, the reciprocal or the negative of the objective function can be used, with the addition of a sufficiently large constant. The number of particles n is typically determined based on the number of decision variables, usually set to 6-8 times the number of tasks. Increasing the number of particles beyond a certain point has little impact on the algorithm's performance. To avoid premature convergence to local optima, the number of overlapping particles is generally set to 1–2. The number of iterations k depends on the complexity of the model and the desired accuracy. The stopping criterion is usually the minimum descent criterion. The iterative process is outlined in Fig. 3.

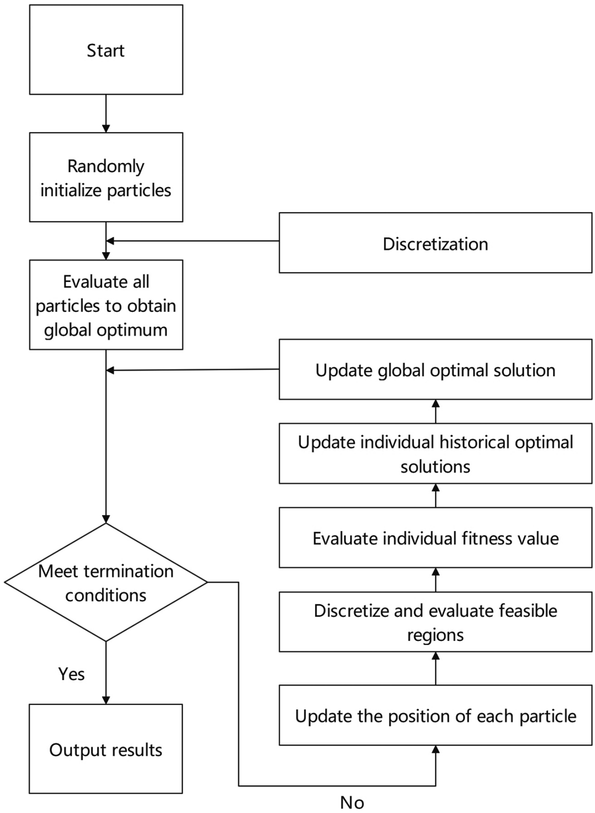

Fig. 3. Flow chat of DPSO

Step 1: Randomly generate n massless particles as initial solutions to simulate individuals in a bird flock. Classify the stopping situation into two categories using the sigmoid function, round up the number of vehicles dispatched, and record the extreme value Pbestik for all individuals in the current stage.

Step 2: Simulate the information sharing mechanism of bird flocks and record the current stage discretized population extremum $Gbest^k = \min\{Pbest_i^k\}$.

Step 3: All particles combine $Pbest_i^k$ and $Gbest^k$, and independently search and adjust their positions according to their "self-awareness". In the k-th iteration, they have two properties: velocity V_i^k and position X_i^k. The value and direction of the velocity vector V_i^k are used as the iteration step and direction for particle i in the k-th optimization. The position and velocity after iteration are shown in Eqs. (6.3) and (6.4). After completing the iteration, they go through the sigmoid function again for discretization and boundary constraints to ensure their physical meaning.

$$V_i^{k+1} = \omega \times V_i^k + c_1 \times \mathrm{rand}() \times \left(Pbest\, x_i^k - X_i^k\right) + c_2 \times \mathrm{rand}() \times \left(Gbest\, x_i^k - X_i^k\right) \tag{6.3}$$

$$x_i^{k+1} = X_i^k + V_i^k \tag{6.4}$$

The iterative formula consists of three parts: the first part is the memory item, the second part is the self-cognition item, which reflects the individual's optimization ability, and the third part is the group cognition item, which reflects the collaborative relationship between populations. In the formula, ω is the inertia factor; $Pbest_i^k$ represents the position corresponding to the individual extremum obtained by particle i after k iterations; $Gbest^k$ represents the position corresponding to the population extremum obtained after k iterations; c_1 and c_2 is the acceleration factor; rand() is a random number.

Step 4: Repeat steps 1 and 2 to calculate and find the updated global optimal value $Gbest^{k+1}$.

Step 5: Verify if the shutdown criteria are met. If yes, output the result; otherwise, return to Step 3.

7. Conclusions

This study focuses on addressing abnormal events in rail transit by developing an emergency dispatch model for connecting public transportation. This model integrates theories and methods that consider the classification of abnormal events and passenger travel behavior. The objective is to offer theoretical support for the collaborative optimization and scheduling of multiple transportation modes during rail transit disruptions. By analyzing the emergency shuttle service process and identifying key factors, a shuttle bus emergency dispatch model was formulated for both single-line and multi-line emergency scenarios, incorporating passenger travel behavior and vehicle operation modes. The decision variables include the stopping plan, dispatch quantity, and departure frequency, aiming to minimize total passenger travel time. The model accounts for resource, time, demand, safety, and physical constraints. Given the integer constraints on the number of dispatched vehicles and stopping plans, a solution process using Discrete Particle Swarm Optimization (DPSO) was designed to solve the model effectively.

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