Analysis of Fire Characteristics and Emergency Evacuation Influencing Factors in Urban Railway Transportation

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Abstract. This paper addresses the characteristics of urban rail transit fires and proposes a predictive model combining evacuation simulation and random forests for rapid forecasting of evacuation targets. Firstly, the characteristics of urban rail transit fires and key factors affecting evacuation are analyzed. Secondly, a three-dimensional model for crowd evacuation simulation is constructed. Finally, a predictive model based on random forests is developed, with an analysis of the importance of predictive variables. The random forest approach can effectively deal with complex nonlinear relationships and large amounts of data, and improve the prediction accuracy and robustness of the model. The results indicate that this method can rapidly predict emergency evacuation scenarios in urban rail transit fires, achieving an accuracy of 95%.

Keywords: component; urban railway; fire risk; emergency evacuation; random forest

1 Introduction

Urban rail transit has become one of the main modes of daily travel for urban residents, and due to its high passenger volume and confined space, urban rail transit systems are exposed to potential fire risks [1]. Urban rail transit systems face potential fire risks, which not only poses a serious threat to public safety, but also leads to large-scale property loss and social panic. Fire characteristic analysis is a crucial component of fire risk assessment. Machine learning models, trained on extensive data, can predict the likelihood and impact of fires. Emergency evacuation is a key measure to ensure passenger safety during fires. Numerous factors influence emergency evacuation in urban rail transit. Analyzing these factors can optimize evacuation plans, enhance efficiency, and minimize passenger harm.

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The introduction of documents such as the "Urban Rail Transit Operation Safety Management Regulations" and the "Urban Rail Transit Safety Production Management Measures" explicitly emphasizes the need to strengthen safety management and the development of emergency response plans for urban rail transit.

This paper discusses the characteristics of urban rail transit fires and introduces the application of machine learning in fire risk analysis. Secondly, it analyses the main factors affecting emergency evacuation in urban rail transit. In addition, exploring the specific implementation of emergency evacuation and its effects by constructing a random forest model for evacuation in fire scenarios. Lastly, summarizing the research findings and providing suggestions for fire prevention and control and emergency management in urban rail transit.

2 Characteristics of Urban Rail Transit Fires and Machine Learning Models

2.1 Characteristics of Urban Rail Transit Fires

The fire characteristics of urban rail transit systems are significantly different from those of other types of buildings and modes of transport due to their special structure and operating environment. Fire causes are diverse, including electrical faults, equipment failures, human factors, and external fire sources [2]. Specifically, urban rail systems rely on electric power, where cable short circuits, equipment overload, and aging electrical components frequently cause fires. Equipment failures, such as overheating mechanical parts and friction-generated heat, can also ignite fires. Human factors involve improper use of open flames, smoking, and carrying flammable or explosive materials. External fire sources, such as fires in surrounding buildings spreading to the transit system, can also trigger fires.

The development of fires is rapid, accompanied by the production of large amounts of smoke and toxic gases. Due to the enclosed environment of rail transit, flames and smoke can quickly spread along tunnels and carriages, accelerating the fire's growth and posing significant challenges to passenger evacuation and rescue. Rapid response and control in the early stages of a fire are crucial to preventing its spread.

The prevention and control of urban rail transit fires require various measures, including the installation of automatic fire alarm systems, automatic fire suppression systems, and smoke control systems, which can detect fires early and implement appropriate measures, reducing damage and casualties.

3 Application of Machine Learning to Fire Risk Analysis in Urban Rail Transport

With the continuous improvement of the urban railway network, the passenger flow is gradually increasing, which lead the occurrence of incidents such as fires becomes a concern. In such emergencies, passengers experience panic and engage in uncontrollable behaviors, potentially leading to unsafe incidents and severe consequences for life and property. Therefore, simulating scenarios like fires in advance is beneficial for preparing emergency evacuation plans, which includes planning the layout of station facilities and equipment, as well as implementing measures for station staff to effectively and safely guide passengers. These efforts aim to minimize risks, enhance the station's capability to evacuate passengers during emergencies, and support safe operations of the station.

Many scholars use simulation to study subway evacuation during emergencies, which has become an effective way to study emergency evacuation. While the complexity of independent variables and the difficulty of determining the key variables in the evacuation of dense crowds are still research difficulties. Machine learning algorithms offer solutions to these challenges. Algorithms like Bayesian networks (BN), support vector machines (SVM), random forests (RF), gradient boosting machines (Light GBM), and convolutional neural networks (CNN) can construct evacuation models that depict relationships between objectives and influencing factors [3]. Compared to SVM, CNN training processes are more intricate and time-consuming. Random forest, a Bagging-based ensemble learning method, effectively handles high-dimensional datasets. By introducing randomness, RF achieve high predictive accuracy [4].

4 Analysis of Factors Affecting Emergency Evacuation in Urban Rail Transit

4.1 Human Factors

The number and density of passengers is a key factor in the speed of emergency evacuation. During peak hours, the density of passengers in carriages and on platforms is extremely high, increasing the difficulty and time of evacuation. Crowded crowds are prone to cause trampling accidents and secondary injuries. Therefore, reasonable control of passenger flow and density is an important means to improve the efficiency of emergency evacuation.

Passengers' behaviour and psychological reactions have an important impact on the evacuation process in emergency situations, and when a fire occurs, passengers may panic, follow blindly, avoid danger and other behaviours, affecting the evacuation speed and efficiency [5]. Passengers' safety awareness and emergency response knowledge are also important factors, and passengers who lack emergency response knowledge may not be able to correctly select escape routes or use evacuation facilities. Passengers' emergency response ability can be improved through publicity and education and regular drills.

4.2 Facility Factors

The quantity, distribution, and width of evacuation pathways and exits directly influence evacuation efficiency. Poorly designed or insufficient pathways and exits can create bottlenecks, prolonging evacuation times. According to relevant standards, urban rail transit systems should be equipped with an adequate number of evacuation pathways and exits to ensure unobstructed flow.

Effective evacuation guidance systems include facilities such as voice announcements, directional signs, and emergency lighting. These facilities help guide passengers to evacuate in an orderly manner during fires, preventing chaos caused by panic. The reliability and coverage of evacuation guidance systems are critical factors affecting evacuation effectiveness, necessitating their reliable operation during emergencies.

4.3 Environmental Factors

Smoke and toxic gases produced during fires are critical factors affecting evacuation. Smoke reduces visibility, making escape more difficult, while toxic gases pose a threat to passengers' lives. Urban rail transit systems should be equipped with efficient smoke extraction and ventilation systems to promptly remove smoke and toxic gases, ensuring the safety and accessibility of evacuation pathways [6]. Additionally, high temperatures can damage evacuation facilities and increase the difficulty of passenger escape. Using heat-resistant materials and facilities, and designing evacuation plans to accommodate high-temperature environments, are essential measures to ensure passenger safety.

4.4 Management Factors

Emergency plans should outline detailed responses, evacuation procedures, and division of responsibilities in the event of emergencies such as fires. Regular drills should be conducted to test the feasibility of these plans, identify and address issues, and enhance the emergency response capabilities of passengers and staff. During emergency evacuations, the response and guidance abilities of personnel are crucial. Urban rail transit operators should enhance training for staff to ensure familiarity with emergency plans, evacuation procedures, and essential emergency response skills. Training should encompass fire alarms, evacuation guidance, passenger reassurance, and first aid knowledge, among other necessary skills.

5 Emergency Evacuation Modelling for Urban Rail Transit in Fire Scenarios

AnyLogic is a dynamic simulation software based on the social force model, featuring intelligent agents and continuous microscopic simulation. It can calibrate model parameters for pedestrians and facilities according to real-world scenarios. Research by Mandal et al. [7] found that AnyLogic effectively simulates evacuation times and has been widely applied in various evacuation scenarios. In this study, an evacuation model was established using the pedestrian library in AnyLogic to simulate multiple influencing factors in the evacuation of urban rail transit stations during fire scenarios, thereby constructing a predictive model database.

Different influencing factors have varying importance for predictive variables. The Random Forest regression model not only predicts safe evacuation time but also provides importance scores for each variable and assesses the impact of inputs on outputs. Therefore, the importance analysis of Random Forest can be used to measure the impact of various influencing factors on evacuation time.

Random Forest measures the predictive strength of each variable using out-of-bag (OOB) samples. For each decision tree in the model, OOB sample data is passed down the tree to generate predictive accuracy. The same process is executed after permuting the input variable. The difference between these two values (predictive accuracy) is averaged across all trees and used as the importance measure for that variable

The importance Ik of an input variable in the tree of number k is calculated as follows: randomly select samples and compute the OOB prediction error rate, then randomly permute the samples and recompute the OOB prediction error rate, and finally compute the difference between the two OOB error rates. The formula for calculating the importance score I(xj) of variable Xj importance Ik in the whole random forest is shown in formulas (1) and (2).

$$I_k(x_j) = \frac{\left[\sum_{n=1}^{N_{OOB}} I(f(x_n) = f_k(x_n)) - \sum_{n=1}^{N_{OOB}} I(f(x_n) = f_k(x'_n)) \right]}{N_{OOB}} \tag{1}$$

$$I(x_j) = \sum_{k=1}^{K} I_k(x_j) / K \tag{2}$$

According to the RF model, an importance analysis was carried out to obtain the order of importance of each influencing factor on the evacuation time. X1 is the personnel factor, X2 is the facility factor, X3 is the environmental factor, and X4 is the management factor, and the results are shown (Fig.1):

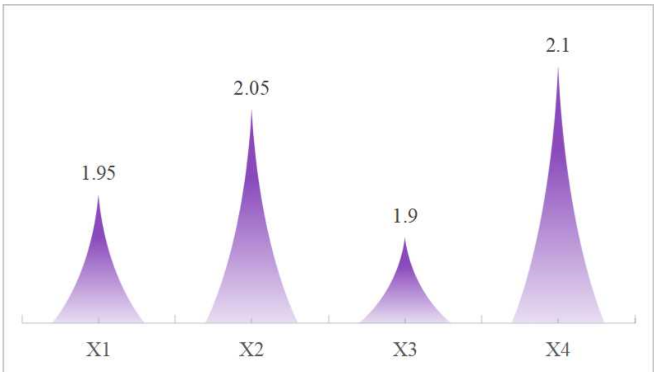

Fig. 1. Level of importance of various influences

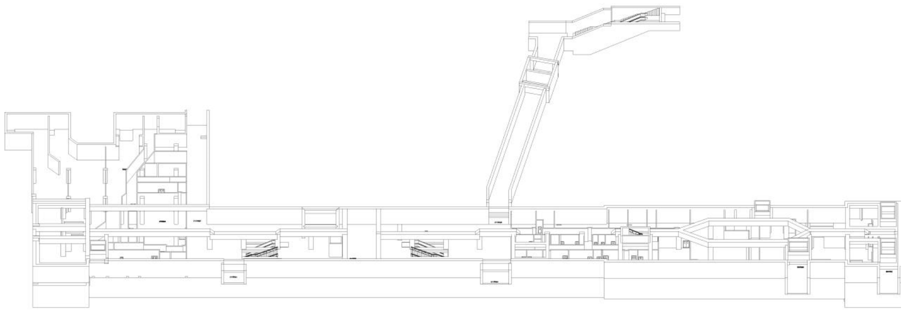

Fig. 2. Basic layout of Aixi Lake West StationCase Study

Aixi Lake West Station is located within the block north of the intersection of Beijing East Road and the planned Yaohu Avenue. The station's net total length is 214.700 meters, with a standard section width of 17.600 meters. The station has four exits situated in the four quadrants of the intersection of Beijing East Road and Yaohu Avenue. Exit 1 was canceled, and Exit 3 was postponed. There are three groups of six ventilation shafts, all of which are open low ventilation shafts. Additionally, there is one fire exit located in the green belt in the northwest quadrant of the intersection (Fig.2).

The evacuation time has been selected as the evacuation target, as longer evacuation times increase panic and the probability of unsafe incidents. RF evacuation time prediction model is constructed, using 40 simulation results as the training set and 10 simulation results as the test set. The evacuation time is determined to be 127.6 seconds. Tvalidate the accuracy of the prediction model, the experimental results are fitted, and the accuracy test results of the model are shown in Table 1.

Table 1. Model validation result

Training set data			Test Set Data		
MAE	***RMSE***	***R^2***	***MAE***	***RMSE***	***R^2***
11.7	14	0.93	12.5	16.1	0.95

According to Table 1, the predictive model is well fitted, with a coefficient of determination R2 of 0.95, indicating that the deviation between the predicted and simulated values is small (the closer the R2 is to 1, the higher the predictive accuracy of the model).

The results indicate that the model constructed in this study can provide reliable and accurate evacuation results. The prediction of safe evacuation time of urban rail through the model is beneficial for urban rail operation and maintenance managers to carry out evacuation safety assessment.

6 Conclusion

This paper combines the evacuation simulation model and Random Forest algorithm to predict the evacuation time in case of fire by taking the crowd in an urban railway station as an example. The model coefficient of determination R2 is 0.95, which shows good correlation and high prediction accuracy. Through the random forest importance analysis, it can be seen that the importance of the influencing factors of the evacuation time is ranked as follows: management factors > facility factors > personnel factors > environmental factors. The results of the study provide a reference for the safe evacuation of crowds in the fields of public safety and emergency management.

In this paper, the selection of emergency evacuation factors is supported by data, but there are still some limitations. Future research could expand the dimensions of emergency evacuation influencing factors and further refine them to more accurately identify evacuation priorities under urban rail transit fire risk conditions, which is helpful for the relevant managers to formulate a more accurate plan.

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