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Study Numerical Simulation of Smoke Movement and LSTM-Based Early Warning for metro Platform Fires

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Abstract: This study systematically investigates smoke spread and visibility changes during metro platform fires, integrating numerical simulation, full-scale smoke tests, and deep learning methods. Based on the Fire Dynamics Simulator (FDS), multiple platform fire scenarios were designed and analyzed, focusing on the effects of smoke extraction modes, Platform Screen Doors (PSDs), and additional platform exhaust fans on smoke dispersion. A Fire in Metro (FIM) database was established using the FDS simulation data. Concurrently, full-scale smoke tests were conducted at an operating metro station in China to validate smoke propagation paths, obtain the timing parameters of metro fire emergency responses, and support parameter settings for numerical simulations. Utilizing the FIM database, a Long Short-Term Memory (LSTM)-based early warning model for smoke visibility in metro fires was developed. The model demonstrated excellent performance on the test set, achieving over 98% accuracy and precision, and successfully triggered alarms for all 118 fire incidents where visibility dropped below the critical threshold, with 33.9% of these incidents predicted in advance. The findings provide theoretical support and technical references for metro platform fire rescue decision-making, smoke control system optimization, and early warning.

Keywords: Full-scale experiment; Platform fire; Smoke control strategy; CFD; Transportation safety

1. Introduction

The metro system plays a vital role in modern cities, offering fast, reliable, and convenient transportation. As a result, it has become the preferred mode of daily travel for many urban residents[1]. With increasing economic development and a growing urban population in the 2020s, the pressure on city transportation systems has intensified, leading to an urgent and escalating demand for underground rail transit. Nowadays metro systems have experienced rapid global development, particularly in megacities such as New York and London. To be specific, New York hosts over 472 metro stations[2], while London's metro system comprises 272 stations[3]. 58 cities in mainland China have opened a total of 361 urban rail transit lines, with a cumulative total of 6,651 operational stations by the end of 2024 [4]. Among them, the Beijing metro system comprises 522 stations across 29 lines, including key routes such as the Airport Express[5]. Underground rail transit offers significant advantages in alleviating urban traffic congestion while enhancing travel efficiency and comfort[6]. It operates independently of weather conditions and maintains extended service hours, thereby meeting the growing demand for urban mobility[7]. However, alongside the rapid development of metro construction, safety risks have become critical concerns. Given that metro systems are primarily located in confined underground spaces with high passenger volumes, they are vulnerable to large-scale evacuations[8], terrorist attacks, and failures in power and signaling systems[9], all of which could lead to substantial negative societal impacts[10]. For instance, in March 2020, an arson attack in the New York City subway resulted in one fatality and 16 injuries[11]. In 2017, the Tsim Sha Tsui subway arson incident in Hong Kong injured 18 people[12]. Additionally, In March 2010, a series of explosions occurred during the morning rush hour at Moscow's Lubyanka and Park Kultury metro stations, resulting in over 140 fatalities and disrupting the commute of approximately 500,000 passengers[13].

In underground building spaces, fire smoke is the primary threat to human life safety[14]. Metro stations are typically located at depths ranging from 10m to 30m. Such depths result in stations being influenced by the surrounding structural environment and lacking natural ventilation. Consequently, in emergency situations such as fires, the absence of natural ventilation hampers smoke evacuation and evacuation speed, making it difficult to clear smoke from underground areas within a short time. Fires involving combustible materials

inside metros, such as cables, passenger luggage[15], or new transportation fire loads like power banks[16],
produce large quantities of toxic gases, including carbon monoxide (CO), carbon dioxide (CO₂) and cyanide[17], which rapidly spread throughout the metro station[18]. The vertical openings connecting platforms
to concourses and concourses to the surface generate upward buoyant forces, exacerbating both the vertical
diffusion and horizontal spread of smoke. Some countries' metro design codes explicitly require the inclusion
of smoke control systems, including smoke detectors, smoke exhaust fans and other smoke control systems in
underground stations by Fire Protection Design Code for Metro Systems in China[19]. However, due to the
complexity of metro station structures and the presence of multiple interlinked systems, improper configura-
tion of fire pressurization and smoke extraction logic may not only fail to promptly remove smoke but also
aggravate the spread of toxic gases. Furthermore, differences in smoke control design philosophies across
countries have led to varying smoke management strategies. Metro systems in China and Singapore generally
adopt platform screen doors (PSDs) that fully enclose the platform-track interface, requiring stringent door
operation strategies during fires to create two distinct smoke control zones[21][20]. In contrast, systems such
as those in New York and London typically feature open platforms without PSDs[22].

Researchers and universities have investigated the impact of different PSD designs on the effectiveness
of smoke control in subway systems. The primary research methods include numerical simulations and scaled
model experiments, while full-scale experimental studies have been conducted only for a limited number of
specific engineering cases[23]. Tsinghua University employed numerical simulation methods to evaluate the
smoke control effectiveness of half-height and full-height PSDs in underground spaces. Based on typical fire
sizes of 3.0 MW and 7.5 MW, the study systematically assessed the influence of various PSD types on smoke
control performance in platform areas, and further proposed optimal ventilation control strategies tailored to
platform fires, carriage fires, and train fires respectively[24]. The Technical University of Civil Engineering
Bucharest developed a CFD model for a metro station equipped with PSDs. Based on the simulation results,
the study focused on the impact of PSDs on smoke behavior during platform fires and employed a modeling
approach to determine CO and CO₂ concentrations within the computational domain based on predefined fire
scenarios[25]. In addition to numerical simulation studies, with the ongoing advancement of metro station

construction in recent years, relevant research institutions have conducted full-scale experimental tests on typical stations. These studies primarily focus on analyzing smoke propagation characteristics and the performance of smoke control systems under various fire scenarios[26][27]. Specifically, Tsinghua University employed hot smoke experiments using a 0.25 MW simulated fire source in a tunnel environment with open PSDs. 3 ventilation conditions, natural smoke exhaust, single-sided transverse velocity flow (TVF) exhaust and double-sided TVF exhaust, were comparatively investigated. The experimental results indicate that, compared to other conditions, the double-sided TVF smoke exhaust scheme demonstrates superior smoke removal efficiency[28]. Chongqing University conducted 3 sets of hot smoke experiments in a typical metro station. Coupled with Fire Dynamics Simulator (FDS) numerical simulations, the study systematically investigated key parameters including smoke layer thickness, CO concentration, smoke control system activation characteristics, and smoke flow patterns[29].

In recent years, the application of machine learning for fire smoke control in transportation has become a growing trend[30]. University of Science and Technology proposed CAERES-DNN, a deep neural network model that leverages FDS simulation data of metro tunnel fires to achieve real-time prediction of smoke visibility distribution and spread distance[31]. Hong Kong Polytechnic University developed a coupled deep learning framework combining Long Short-Term Memory (LSTM) networks and Transposed Convolutional Neural Networks, enabling real-time prediction of spatial temperature fields in tunnel fires within 1 second and forecasting up to 60 seconds ahead with a prediction accuracy of 97%[32].

Currently, most related studies focus on fixed smoke extraction systems or natural ventilation within metro stations. This study takes platform fires as an example and proposes a hybrid smoke control strategy that integrates the use of mobile smoke exhaust fans to assist ventilation during underground firefighter rescue operations. The proposed strategy is compared with conventional smoke control methods. Furthermore, a series of investigations on smoke behavior in platform fires are conducted based on full-scale fire experiments and machine learning techniques.

The paper is structured into four main sections. The first section serves as an introduction, outlining the background and significance of metro fire research, comparing metro design differences across multiple

countries, and highlighting numerical simulation, full-scale fire experiments, and machine learning as the primary technical approaches currently employed in this field. The second part focuses on the research methodology, proposing an improved smoke control strategy for optimizing metro smoke management and a fire prediction model, alongside detailed descriptions of the numerical simulation parameter settings and experimental conditions. The third part presents data analysis and discussion, validating the reliability of the simulation methods through comparison with experimental results, and systematically comparing the smoke control effectiveness of three different ventilation schemes; additionally, fire characteristic data are further mined using repeated simulations and machine learning techniques. The fourth part concludes the paper with key findings and outlines future research priorities and development directions.

2. Methods

In this study, the smoke movement characteristics of metro platform fires are investigated through a combined approach of numerical simulation, hot smoke experiment, and deep learning.

2.1 Numerical Simulation

2.1.1 Computer-based Metro Modeling

The computational model developed in this study is based on an in-service metro station located in southern China, where hot smoke tests have previously been conducted. Under the actual engineering conditions of the station, two computer-based models of a double-island metro station were established using PyroSim[33], as illustrated in Figure 1. The station adopts a 2-level underground island, with a total length of approximately 215.0m and a standard section width of 19.7 m. The first underground level serves as the concourse level, with a public area of approximately 1,594 m² and a floor height of 5.6 m, and is equipped with four entrances providing direct access to the ground. The second underground level functions as the

platform, which can accommodate two trains simultaneously. The effective platform width and length are 11 m and 120 m, respectively, with a public area of approximately 928 m² and a floor height of 5.25 m.

The primary distinction between the 2 physical models is the PSDs, which leads to fundamentally different platform configurations. Figure 1(a) represents a typical Chinese metro platform equipped with PSDs, where the doors remain closed during normal operation and are opened only for passenger boarding and alighting or in emergency situations. In contrast, Fig. 1(b) depicts a U.S. metro station prototype with a fully open platform, in which the track and platform areas are directly connected without any physical separation by PSDs.

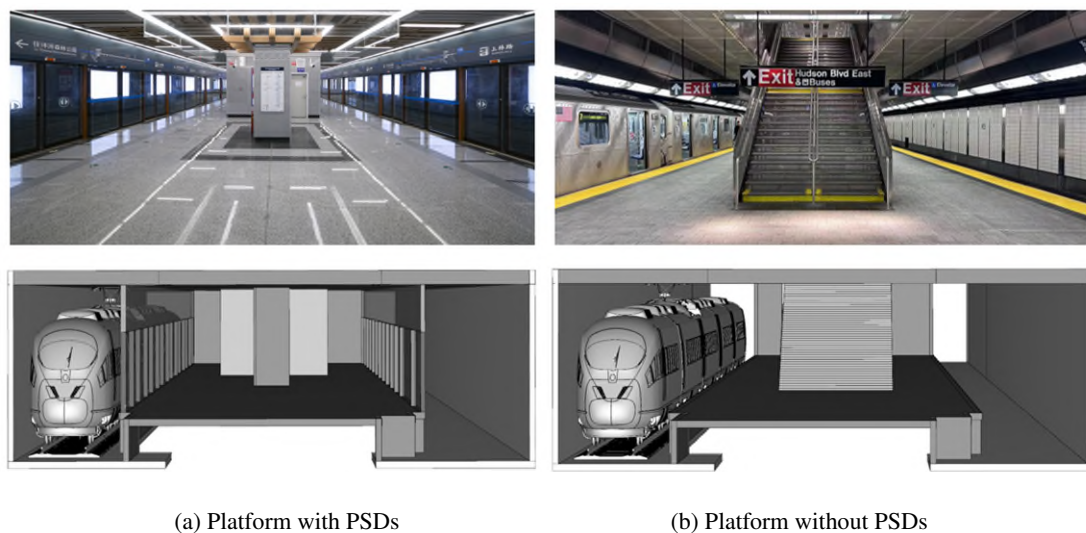


Figure 1. Comparison of Typical Metro Platform Models (with and without PSDs)

2.1.2 simulation scenarios

Based on an analysis of the differences in platform and track area separation configurations and smoke exhaust modes in China and US metro stations, a concept of using mobile devices to induce smoke extraction was proposed. Accordingly, 3 numerical simulation scenarios were designed and fire simulations were conducted using FDS. The parameters of the simulation scenarios are listed in Table 1. The activation times of related systems are based on experimental data, and the supply airflow rate of fans are set according to the

respective design guidelines. To minimize the influence of stochastic simulation data on the results, each scenario was simulated twice with a fire duration of 900 s.

To comprehensively analyze the horizontal and vertical dispersion characteristics of smoke within the model, three smoke monitoring visualization slices were established. Among these, one horizontal slice was set at a height of 2 meters above the ground, while two vertical slices were positioned at 1.5 meters inside the tunnel on the PSD side and 1.5 meters on the platform side outside the PSD, respectively.

Table 1. Simulation Parameters for Platform Fire Scenarios

Fire Scenario	I	II	III
	Mechanical Smoke Exhaust	Hybrid Smoke Exhaust	Natural Smoke Exhaust
PSDs	$T_{\text{active}}=84\text{s}$	$T_{\text{active}}=84\text{s}$	-
PyroSim Model	Platform with PSDs	Platform with PSDs	Platform without PSDs
Mobile Smoke Exhaust Fan	-	$V=109,776\text{ m}^3/\text{h}$	-
Platform Smoke Exhaust System	$T_{\text{active}}=55\text{s}$ $V=55,680\text{ m}^3/\text{h}$	$T_{\text{active}}=55\text{s}$ $V=55,680\text{ m}^3/\text{h}$	-
Total Smoke Exhaust Volume in Tunnel	$T_{\text{active}}=109\text{s}$ $V=144,000\text{ m}^3/\text{h}$	$T_{\text{active}}=109\text{s}$ $V=144,000\text{ m}^3/\text{h}$	-

*The activation times of the systems shown in the table are based on the hot-smoke test.

2.1.3 Parameter Settings

Based on a grid sensitivity analysis, a uniform mesh with a resolution of $0.25 \times 0.25 \times 0.25\text{ m}$ was adopted in FDS[34]. The fire growth was prescribed as a fast-growing fire following a $Q = at^2$ curve [35], reaching a steady-state heat release rate of 3 MW and the fire growth rate is 0.044 kW/s^2 . To facilitate a focused comparison of the smoke control performance under the three scenarios, the smoke production characteristics of polyurethane were adopted in the simulation, with a soot yield of 0.113 and a CO yield of 0.024. According to the metro smoke control design guidelines, the exhaust airflow rate at the platform level was set to $55,680\text{ m}^3/\text{h}$, while the tunnel exhaust rate was specified as $144,000\text{ m}^3/\text{h}$. In the numerical simulations, the activation

times of the PSDs, smoke exhaust fans, and other related devices were determined based on the results of full-scale fire experiments.

2.2 full-scale experiment

2.2.1 Experimental Site

A full-scale fire experiment on smoke control and ventilation at a metro platform was conducted during non-operational nighttime hours. The building characteristics of the experiment station have been described in Section 2.1.1. At the platform level, fully enclosed PSDs were installed between the platform and the track area, with 24 doors arranged on each side.

2.2.2 smoke exhaust strategy for platform fire

When a fire occurs in the platform, the metro control room automatically shuts down the station's regular ventilation system upon receiving the fire alarm and activates the platform smoke exhaust system. After confirmation by the operations control center that no trains are approaching the station, the PSDs on the fire-affected side and the station tunnel ventilation system are activated, along with the tunnel exhaust outlets located at the tunnel crown on that side. The metro tunnel is equipped with 13 groups of exhaust outlets on one side, each outlet measuring 1000 mm × 500 mm, with every 3 outlets forming a group. A total of 13 groups, comprising 39 individual outlets, were involved in this hot-smoke test. Smoke from the platform is transported through the PSDs into the tunnel and discharged outdoors via the exhaust outlets at the tunnel crown.

2.2.3 Experimental Setup and Test Condition

The test was conducted following the Australian Standard Smoke Management Systems-Hot Smoke Test[36], selecting the maximum fire load specified, which consists of four 0.5 m² A1 trays with a total fire

size of approximately 1.5 MW. The experiment focused on evaluating the activation of the smoke control system and its effectiveness in smoke extraction after a platform fire. Airflow velocity at the stairwell cross-section and PSDs were measured using both handheld and inline anemometers, while an Image Capture System (ICS) was employed to observe the smoke extraction performance on the platform level in real time.

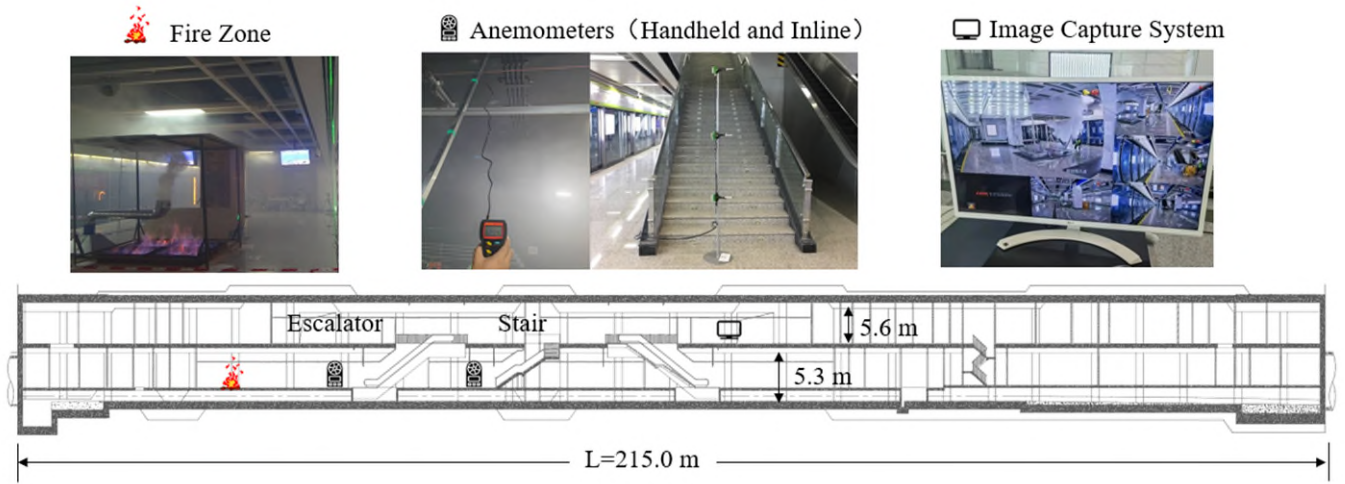


Figure 2. diagram of the hot smoke test for a platform fire.

2.3 LSTM-based early warning model for platform fire

The Fire in Metro (FIM) database was developed using numerical simulation results generated by FDS. The database primarily comprises 6 data sets, each containing synchronized measurements of CO, CO₂, and visibility from 20 monitoring points distributed throughout the platform of metro. Consequently, each data set consists of 60 synchronous channels, 20 points $\times$ 3 variables, along with corresponding timestamps. For each fire scenario, the simulation was conducted for 900 s after ignition with a temporal resolution of 1s, resulting in 901 time steps per scenario. Across all 6 scenarios, a total of 5,406 time steps were obtained for subsequent data analysis and model development.

2.3.1 Data preprocessing methods

Using the FIM database, the most representative CO, CO₂ and visibility indicators were identified and
 utilized for the development of an early warning model. Let $x_i(t)$ denote the observation vector at the i -th
 monitoring point at discrete time step t :

$$x_i(t) = \begin{bmatrix} CO_i(t) \\ CO_{2,i}(t) \\ Vis_i(t) \end{bmatrix} \in R^3 \quad (1)$$

In which $CO_i(t)$ and $CO_{2,i}(t)$ represent the volume fractions of carbon monoxide and carbon dioxide
 at the i -th monitoring point and time step t , with units of ppm and %, respectively. $Vis_i(t)$ denotes the
 visibility in meters. The sampling interval throughout the model is 1 s.

Based on the FIM database, a binary classification early warning task was performed[37], where the
 classification label y_i is defined as follows:

$$y_i(t) = \begin{cases} 1, & \exists r \in \{t+1, \dots, t+T\}, H_i(r) = 1 \\ 0, & otherwise \end{cases} \quad (2)$$

Where T denotes the prediction horizon. In this study, $T = 30s$. $H_i(r)$ serves as the hazard indicator,
 with its definition and judgment criteria detailed as follows:

$$H_i(t) = \begin{cases} 1, & CO_i(t) \geq CO_{crit} \vee CO_{2,i}(t) \geq CO_{2,crit} \vee Vis_i(t) \leq Vis_{crit} \\ 0, & otherwise \end{cases} \quad (3)$$

According to the Available Safe Egress Time (ASET) criteria adopted in fire safety assessment[38], the
 critical threshold values for the three variables are defined as $CO_{crit} = 500ppm$, $CO_{2,crit} = 1\%$, $Vis_{crit} =$
 $10m$.

A sliding window approach was employed to construct samples from the time series at each monitoring
 point. In this study, L was adopted as 60 s corresponding to a 60 s historical window.

$$X_i(t) = [x_i(t - L + 1), x_i(t - L + 2), \dots, x_i(t)] \in R^{L \times 3} \quad (4) \quad 213$$

To increase the sample size, the sliding window was advanced with a step size of s . in this model $s = 5s$ was adopted. After aggregating the samples from all simulation scenarios and monitoring points, feature-wise standardization was performed as follows: 214
215
216

$$\tilde{x}_i(k) = \frac{x_i(k) - \mu}{\sigma} \quad (5) \quad 217$$

Here, μ and σ denote the mean and standard deviation vectors of all training samples, respectively. 218
The dataset was randomly divided into training, validation, and test sets without temporal overlap, with an 219
approximate ratio of 7:1.5:1.5. 220

2.3.2 LSTM Early Warning Model 221

A single-layer LSTM network was employed to construct a many-to-one binary classification model. For 222
the input sequence $X_i(t) = \{\tilde{x}_i(t - L + 1), \dots, \tilde{x}_i(t)\}$, the LSTM units are recursively updated over time as 223
follows: 224

$$(h_i(k), c_i(k)) = \text{LSTM}(\tilde{x}_i(k), h_i(k - 1), c_i(k - 1)) \quad (6) \quad 225$$

$$k = t - L + 1, \dots, t \quad (7) \quad 226$$

Where $h_i(k)$ denotes the hidden state and $c_i(k)$ represents the cell state of the LSTM unit. The hidden 227
state at the final time step, $h_i(t)$ is taken as the sequence representation, which is then fed into a fully 228
connected layer, followed by a sigmoid activation function to obtain the hazard probability: 229

$$z_i(t) = W^T h_i(t) \quad (8) \quad 230$$

$$p_i(t) = \sigma(z_i(t)) = \frac{1}{1 + e^{-z_i(t)}} \quad (9) \quad 231$$

W represents the weight of the fully connected layer. The model output $p_i(t) \in (0,1)$ represents the probability of a hazardous event occurring within the future T seconds following the time corresponding to the input sequence. Given a decision threshold θ , the early warning decision is determined as follows: 232 233 234

$$\hat{y}_i(t) = \begin{cases} 1, & p_i(t) \geq \theta \\ 0, & p_i(t) < \theta \end{cases} \quad (10) \quad 235$$

2.3.3 Loss Function and Threshold Selection 236

Due to the imbalance between positive and negative samples, a weighted binary cross-entropy loss was employed during the training phase: 237 238

$$\mathcal{L} = -\frac{1}{N} \sum_{j=1}^N (w_+ y_j \ln p_j + (1 - y_j) \ln(1 - p_j)) \quad (11) \quad 239$$

Here, N denotes the batch size, and the positive class weight is defined as $w_+ = \frac{N_-}{N_+}$, where N_+ and N_- represent the numbers of positive and negative samples in the training set, respectively. The class weights are set inversely proportional to the sample counts. The Adam optimizer was employed with a learning rate of 10^{-3} , and early stopping based on validation loss was applied to prevent overfitting. To ensure the safety of fire early warning, the decision threshold θ was determined via grid search on the validation set. Following a recall-priority principle, candidate thresholds satisfying the target recall rate were first identified, and the one with the highest precision among them was selected as the optimal threshold θ^* . The final decision rule is: if $p_i(t) \geq \theta^*$, an alarm is triggered. 240 241 242 243 244 245 246 247

3 Results and Discussion 248

3.1 Smoke features parameters 249

As illustrated in Fig. 3, the temporal evolutions of smoke characteristic parameters under 3 fire scenarios were compared based on the FDS simulation results. Taking the monitoring point located near the fire source and approximately 4.6 m from the PDS as an example, the visibility rapidly decreased to 10 m at around 35 s during the period of shown, reaching the high risk level. In contrast, the time at which the CO₂ volume fraction reached the hazardous criterion was significantly delayed by nearly 199 s. The simulation results for CO are more conservative compared to the other two features, consistently remaining within the low risk level in blue. Based on these observations, the most unfavorable visibility parameter was selected as the key indicator to compare the smoke distribution characteristics and smoke exhaust processes under different fire scenarios.

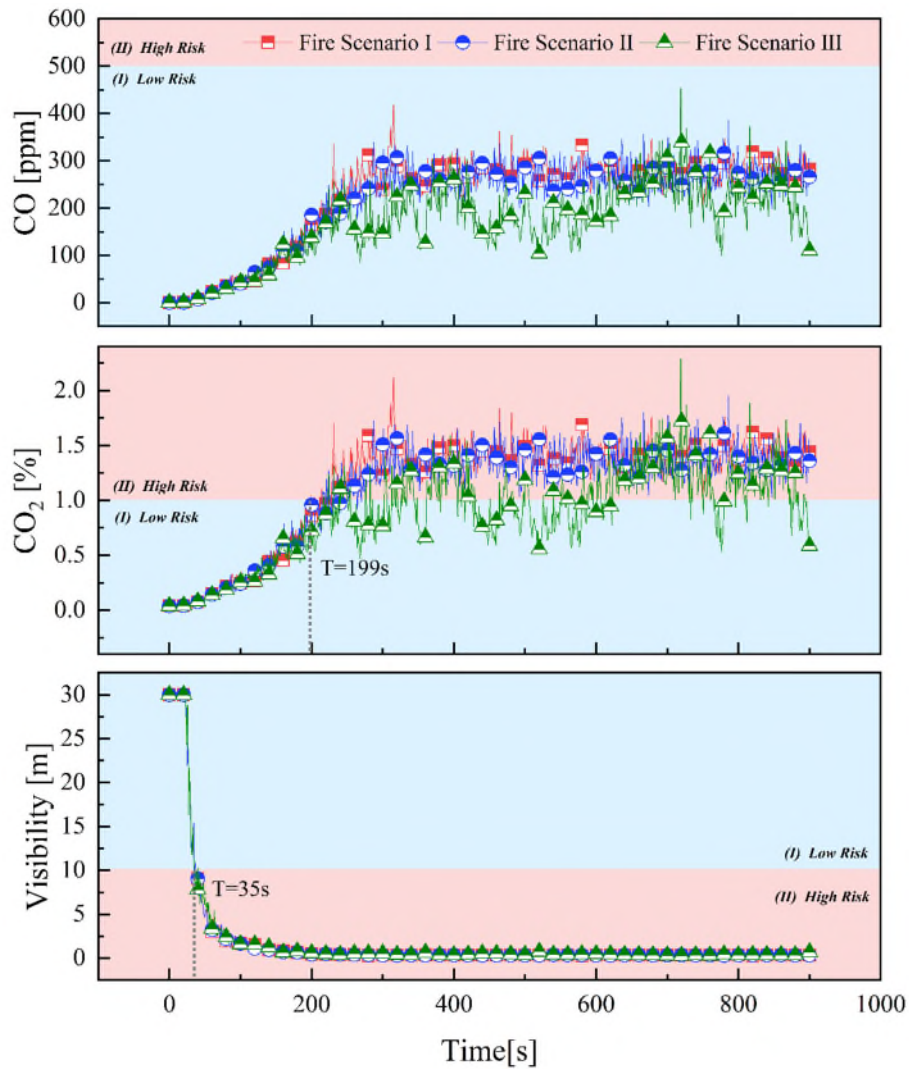


Figure 3. Simulated variations of CO, CO₂, and visibility under fire Scenario I, II, and III

3.2 Phenomenon of Smoke Spread

Figure 4 illustrates the simulated visibility distributions at representative time instants under the 3 fire scenarios at a monitoring location 1.5 m away from the PSDs in the metro station platform area. Combined with the FDS simulation slices and visibility measurements, the spatial evolution of smoke was evaluated. Taking Fire Scenario I as an example, the results showed that smoke mainly accumulated and spread within the platform space, resulting in a gradual reduction in visibility during fire development. After the PSDs were opened, smoke was mainly discharged into the tunnel through the middle and upper parts of the PSDs on one side. Specifically, as shown in Fig. 4(a), at $t = 39$ s, smoke spread horizontally along both sides of the platform, with a propagation length of approximately 9.5 m. Due to the obstruction of the end wall at the left side of the platform, smoke transport was locally restricted, leading to localized smoke descent. At $t = 55$ s, the visibility at a height of $H = 2.0$ m decreased from the initial value of 30.0 m to 25.5 m and subsequently dropped to 9.59 m for the first time after an additional 21 s, corresponding to a reduction in visibility of approximately 68%.

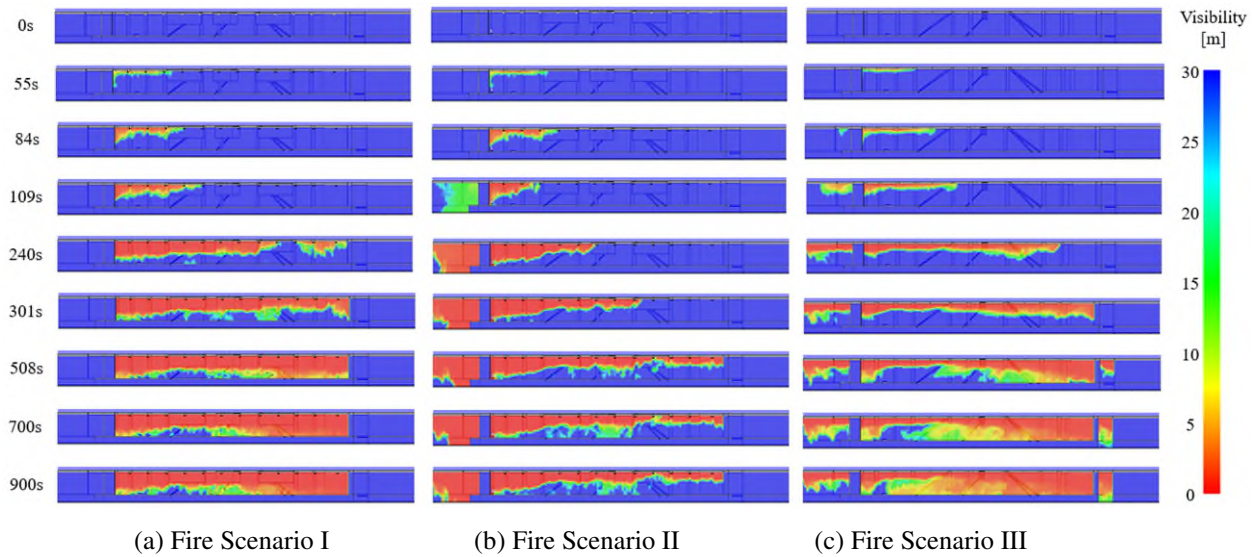


Figure 4. Visibility distributions at representative time instants on the platform side at a distance of 1.5 m from the PSDs under a 3 MW platform fire

With the progression of the simulation, smoke within the platform continued to propagate toward the right side. At $t = 52$ s, 167 s, and 240 s, the smoke front successively reached the staircase located 13.7 m from the fire source, the escalator at a distance of 58.6 m, and the rightmost platform wall, respectively. When the

PSDs were opened at $t = 84$ s, connectivity between the platform and the tunnel was established, allowing smoke to spread into the tunnel driven by buoyancy effects. As shown in Fig. 5(a), at $t = 91$ s, smoke still entered the tunnel mainly through PSDs No. 3, 5, and 6. After the activation of the track-level exhaust duct at $t = 109$ s, a large amount of smoke flowed from the platform into the tunnel through the middle and upper parts of the PSDs and was subsequently exhausted through the tunnel ceiling vents. At $t = 300$ s, it was clearly observed that the visibility in the tunnel region above 4.7 m from the tunnel floor on the left side dropped below 10 m. In the later stage, a smoke exhaust pattern dominated by both sides of the tunnel gradually formed. Throughout the entire 900 s simulation period, no significant smoke descent was observed within the tunnel, and smoke on the platform did not spread to the concourse level.

In fire scenario II, a mobile smoke exhaust fan was added at platform. The simulation results clearly showed that the enhanced and organized airflow effectively suppressed the horizontal spread of smoke within the platform while increasing the smoke concentration in the tunnel. As illustrated in Fig. 5(b), after the activation of the mobile fan at PSD No. 1 at $t = 125$ s, this location became the primary smoke exhaust outlet. Compared with fire scenario I, the smoke discharge pattern changed from being concentrated in the middle and upper portions of the PSD to being distributed over the entire PSD area, which was mainly attributed to the horizontal airflow induced by the fan. As a result, the horizontal propagation of smoke within the platform was significantly inhibited. Compared with fire scenario I, the times for smoke to reach the stair and the rightmost platform wall were delayed by 111 s and 112 s, respectively. Overall, the visibility conditions across the platform were substantially improved. At the rightmost location of the platform at $H = 2.6$ m, the visibility in fire scenario I decreased to 4.1 m at $t = 212$ s, whereas under fire scenario II, the same visibility level was reached until $t = 508$ s.

In fire scenario III, neither PSDs nor mechanical smoke exhaust measures were implemented. The connected volume between the platform and the tunnel reached $10,872 \text{ m}^3$, which was $3,255.2 \text{ m}^3$ larger than that in fire scenario I. The FDS results showed that smoke rapidly spread to the platform ceiling after $t = 13$ s and further expanded into the tunnels on both sides approximately 27 s later. This behavior was primarily attributed to the absence of physical separation provided by the PSDs. Subsequently, the smoke propagation

exhibited typical ceiling jet characteristics. A comparison between Fig. 4(a) and Fig. 4(c) indicated that the overall visibility on the platform in fire scenario III remained higher than that in fire scenario I throughout the entire simulation. This was mainly because, at $t = 52$ s, part of the smoke was driven by buoyancy to rise through the staircase area into the concourse level, thereby reducing smoke accumulation on the platform. Specifically, at the intermediate stage of the simulation ($t = 301$ s), the visibility in fire scenario I decreased to 10 m at the left-side fire source region of the platform ($H = 0.4$ m), the central platform region ($H = 2.1$ m), and the right-side platform region ($H = 0.3$ m). In contrast, at the same time instant in fire scenario III, the visibility at the central platform location was approximately 17 m, while the visibility at the other corresponding measurement points remained at around 30 m. In the later stage of the simulation, as heat exchange intensified and the buoyancy-driven flow weakened, the smoke lost its lifting capacity and exhibited pronounced settling behavior, which was clearly observed in Fig. 5(c).

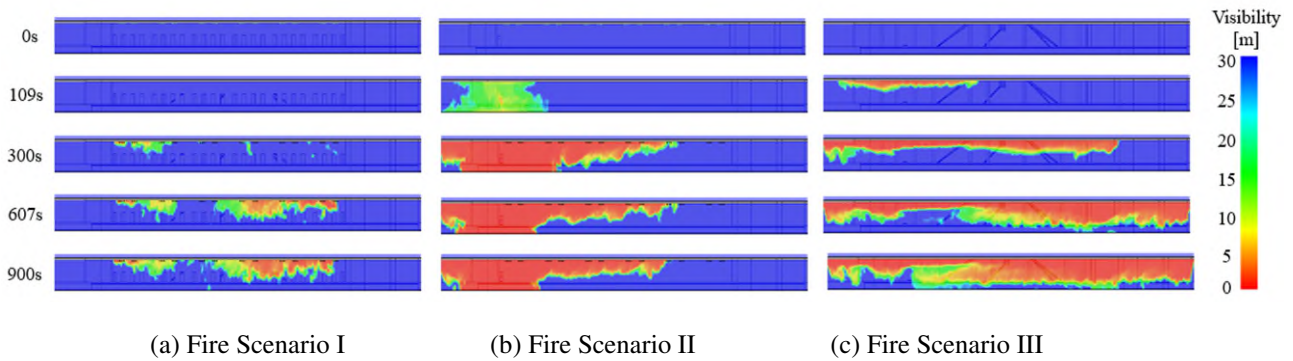


Figure 5. Visibility distributions at representative time instants on the tunnel side at a distance of 1.5 m from the PSDs under a 3 MW platform fire

3.3 Experimental smoke propagation phenomenon

The platform hot-smoke test was conducted to verify the smoke exhaust performance of a metro station design configuration equipped with PSDs, and its smoke control logic is consistent with that of fire Scenario I in simulation. During the test, the ICS comprehensively recorded the evolution of smoke spread in the platform fire. Based on the characteristics of smoke dispersion and fire-driven flow dynamics, the entire process was divided into 6 representative phases, as illustrated in Fig. 6.

In Phase 1, 4 alcohol trays with a total Heat Release Rate (HRR) of 1.5 MW were ignited, leading to the rapid development of a buoyancy-driven thermal plume. Once the plume reached a quasi-steady state, a white smoke generator was activated; at this point, no significant smoke accumulation was observed within the platform. Subsequently, upon entering Phase 2, the white tracer smoke rose rapidly with the thermal plume to the ceiling of the platform level and then spread horizontally under the influence of the ceiling jet. At $t = 55$ s, the smoke detectors on the platform level detected the smoke signal, triggering the activation of the platform smoke exhaust system, while the fire alarm system on the platform level was simultaneously activated. Then, at $t = 84$ s, the 24 PSDs on one side of the platform were opened. As observed in Phase 3, this action established a clear connection between the platform level and the tunnel space. Moreover, the downward airflow induced from the concourse level promoted smoke migration along the ceiling-jet path toward the PSDs.



According to the platform fire smoke control strategy described in Section 2.2.2, 13 groups of exhaust outlets were subsequently activated at $t = 109$ s, and all smoke control systems associated with the platform fire operated as designed. As clearly illustrated in Phase 4, the suction effect induced by the tunnel exhaust fans behind the PSDs resulted in a pronounced one-sided, directional smoke flow in the upper smoke layer, with smoke being effectively guided from the platform into the tunnel. Phases 2 through 6 collectively demonstrate the typical smoke transport behavior following the activation of the platform fire smoke control systems. In Phase 5, the smoke generator continued to release tracer smoke. Under the combined effects of the downward airflow from the concourse level and the tunnel exhaust fans, airflow disturbances were significantly intensified, leading to large-scale descent and mixing of smoke within the platform space. During this phase, the cross-sectional average air velocity in the tunnel was approximately 2.7 m/s, while a downward airflow of about 2.0 m/s was measured at the stair–escalator opening. As shown in Figure 7, the inline anemometers positioned at $H=1.5$ m near both the stairs and escalators consistently recorded a downward airflow velocity of approximately 2.0 m/s, ensuring that the platform maintained a negative pressure condition. Finally, due to the limited smoke-generation duration of the smoke pellets, the smoke concentration gradually decreased during the later stage of the test. With the coordinated operation of the platform and tunnel smoke exhaust systems, the visibility on the platform recovered to its initial level by $t = 289$ s.

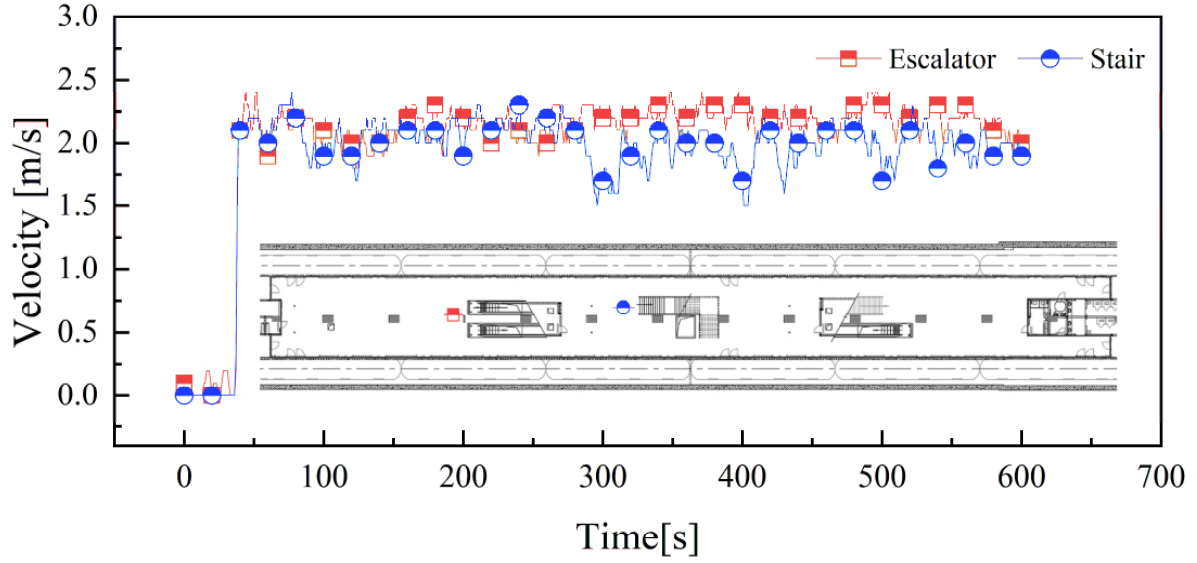


Figure 7. Downward airflow velocity of stair and escalator during the platform smoke test

A comparison between Phase VI and the initial test condition indicates that the smoke within the platform was consistently directed through the PSDs into the tunnel, and no smoke accumulation was observed on the platform when the exhaust fans were operating as designed. This demonstrates that the smoke management system effectively controlled the smoke transport pathways. Moreover, the overall smoke movement pattern shows a high degree of agreement with the FDS results.

3.4 Results and Analysis of LSTM-Based Fire Smoke Early Warning

For the visibility-based early warning task under metro fire scenarios, the test set contained a total of 2,934 temporal windows, of which 91.3% were positive samples corresponding to hazardous conditions occurring within the subsequent 30 s. As shown in Fig. 8, under the recall-priority decision threshold, the LSTM model achieved an accuracy of 98.06%, a precision of 98.92%, a recall of 98.95%, and an F1-score of 0.9894 on the FIM test set, respectively.

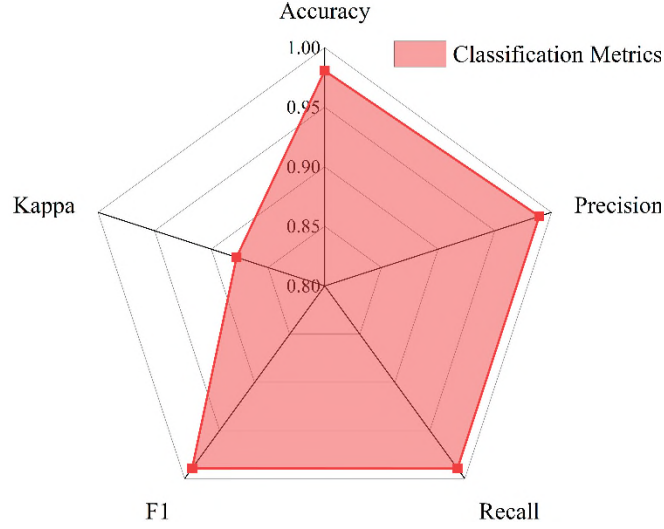


Figure 8. Performance Metrics of the LSTM Model on the FIM Test Dataset

Regarding the curve evaluation metrics [39], as shown in Figure 9(a), the model achieved an AUC-ROC of 0.994 and an AUC-PR of 0.999. In this fire early warning task, true positive rate (TPR) reflects the model's ability to correctly detect hazardous windows, whereas false positive rate (FPR) reflects the probability of false alarms in non-hazardous windows. The detailed confusion matrix distribution is presented in Figure 9-(b), where the true negatives, false positives, false negatives, and true positives are 227, 29, 28, and 2,650, respectively. Based on these data, the miss rate for the danger window is 1.05%, which is lower than the false alarm rate of 11.33%. The model sensitivity and specificity are 0.990 and 0.887, respectively.

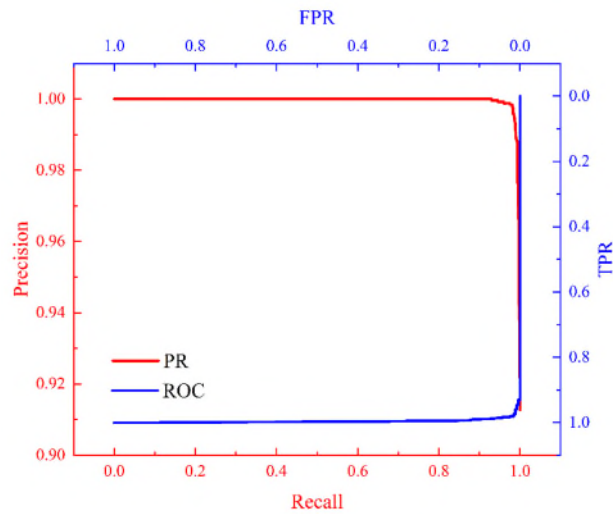


Figure 9. Performance evaluation of the LSTM early warning model on the FIM test dataset

In metro platform fires, the confined spatial structure leads to rapid smoke stratification, where visibility degradation typically precedes temperature rise and toxic gas accumulation. Visibility loss is thus the earliest and most critical hazard factor during such fires. The model achieved a high recall rate of 98.95% and a low miss rate of only 1.05% on the test set, indicating that the LSTM architecture successfully captured subtle temporal features of visibility during the early stages of platform fires.

The overall distribution of the early warning lead time is shown in Figure 10. Statistical analysis indicates that a total of 118 fire incidents met the danger criteria due to visibility dropping below the critical threshold, and the LSTM model successfully triggered alarms for all these hazardous events. Among them, 40 incidents received alarm signals before the visibility reached the critical value, resulting in an early warning coverage rate of 33.9%. The average lead time for these early alarms was 25.9 s, with a median of 11.0 s and a maximum lead time of up to 158 s. Although visibility changes rapidly during fires in platform, causing approximately 45% of early alarms to cluster within the period from 0s to 10s, this time window of several tens of seconds can still be effectively used in large, densely populated metro platforms to initiate emergency broadcasts or switch smoke control modes, thereby mitigating panic and improving evacuation efficiency.

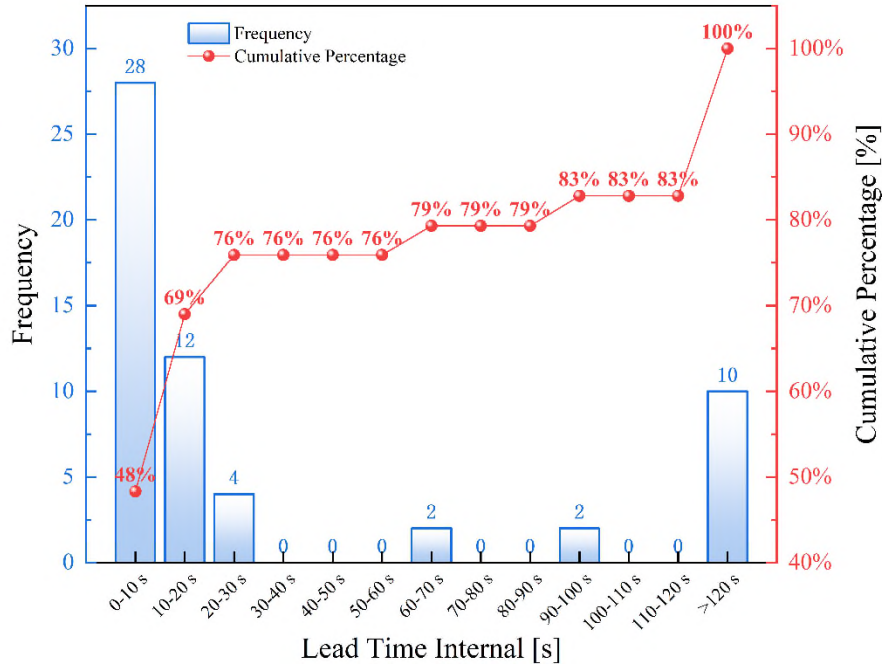


Figure 10. Distribution of early warning lead times internal for platform fire in station

4 Conclusions

This study focuses on fire safety in metro buildings. Numerical simulation methods were employed to comparatively analyze 3 architectural smoke exhaust patterns in metro stations. Based on 3 key smoke characteristic parameters, a platform fire prediction model was developed using an LSTM network. Furthermore, smoke path validation experiments were conducted on typical platforms equipped with PSDs through full-scale fire test in the metro environment. The relevant studies have drawn the following conclusions:

A full-scale platform fire test with an HRR of 1.5 MW was conducted in an operating metro station in China, and the experimental data were used to support parameter determination for subsequent numerical simulations. During the test, the platform smoke exhaust system was activated at 55 s, followed by the opening of the PSDs at 84 s, which established a connection between the platform and the tunnel. The tunnel ceiling exhaust outlets were activated at 109 s. Moreover, Under the combined effects of a downward airflow of approximately 2.0 m/s from the concourse and the tunnel ceiling exhaust fans, smoke on the platform is orderly transported into the tunnel through the PSDs. The results indicate that at $t = 289$ s, platform visibility only

shows a little difference compared with the initial condition. Analysis of the smoke transport paths based on the ICS further confirms good agreement with the corresponding numerical simulation scenarios.

The LSTM-based platform fire smoke visibility early warning model developed in this study demonstrates excellent performance on the FIM test set, achieving an accuracy of 98.06%, a precision of 98.92%, a recall of 98.95%, and an F1-score of 0.9894. Furthermore, for the 118 fire incidents where visibility dropped below the critical threshold of 10 m defined by ASET, the proposed model achieves a 100% alarm activation rate. Among these incidents, 33.9% are successfully predicted in advance, with an average lead time of 25.9 s.

Due to operational constraints of the metro system, this study conducted only a single full-scale platform fire test with an HHR of 1.5 MW and was unable to experimentally validate the synergistic smoke extraction effects of mobile fans and varying fire loads considered in numerical simulation scenario II. Future research will focus on optimizing and validating these aspects in conjunction with firefighting tactics and rescue operations specific to metro environments. Furthermore, considering the computational time constraints required for real-time early warning, single-layer LSTM model architecture was adopted in this study to achieve faster inference and output speeds. Subsequent work will expand the FIM database with additional data from full-scale fire tests and numerical simulations and develop a hybrid deep learning model integrating Transposed Convolutional Neural Networks, Attention mechanisms, and LSTM, aiming to improve the accuracy and reliability of smoke visibility early warning in metro fires.

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• **Data availability:** The datasets used and analysed during the current study available from the corresponding author on reasonable request.

Abbreviations			
PSDs	Platform Screen Doors	ICS	Image Capture System
FDS	Fire Dynamics Simulator	ASET	Available Safe Egress Time
FIM	Fire in Metro	HRR	Heat Release Rate (MW)
LSTM	Long Short-Term Memory	ROC	Receiver Operating Characteristic
TVF	Transverse Velocity Flow	PR	Precision-Recall
CO ₂	Carbon Dioxide	CO	Carbon Monoxide

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