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Research on the Prediction Method of Tunnel Fire Heat Release Rate Based on Informer Network

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Abstract. Due to their relatively enclosed characteristics, tunnels facilitate rapid spread of fire and accumulation of harmful smoke gases, posing a significant threat to the safety of human lives and property. The heat release rate (HRR) is a critical parameter that characterizes the scale and severity of a tunnel fire incident. In order to predict the HRR and meet the demand for rapid real-time feedback in tunnel fire scenarios, this study was conducted on three tunnel fire datasets established through numerical simulations and on-site experiments. Then, a deep neural network model, Informer, was applied to train a predictive model for tunnel fire HRR for the first time based on the datasets mentioned above. The results indicate that this method which applies the Informer model demonstrates high accuracy. In short-term predictions, the R^2 values on multiple tunnel datasets exceeded 0.85. This study contributes to aiding rescue personnel in promptly obtaining information on the subsequent development trends of a tunnel fire incident.

Keywords: Tunnel fire; Heat release rate prediction; Deep learning; Informer neural network

1 Introduction

Tunnels, as a common form of underground space utilization, play important roles in modern society such as transportation, municipal pipelines, and civil defense projects. With the development of society and the advancement of construction technology, the number and length of tunnels in China have continuously achieved breakthroughs, showing a rapid development trend. Due to the long and narrow semi-enclosed nature of tunnels, the characteristics of internal fires differ significantly from fires in above-ground buildings and open spaces, with more obvious temperature and smoke accumulation effects, often causing significant damage. Thus, the fire prevention and firefighting issues of existing tunnels have become important factors affecting tunnel operation safety. This has sparked research interest among numerous scholars both domestically and internationally. For example, Ingason H and Beard A, along with their colleagues, have conducted extensive research on the mechanisms and patterns of tunnel fires, and compiled their findings into comprehensive books[1-2].

In tunnels, the confined space and the disparity between longitudinal and transverse dimensions present a challenge for heat dissipation. Consequently, fires in

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these narrow confines are prone to exhibit a rapid increase in Heat Release Rate (HRR) and reach higher peak values compared to those in open areas. HRR refers to the amount of heat released by material combustion per unit of time under specified conditions. It is a key indicator for assessing the scale and development trend of fires. Vytenis and Richard pointed out that the HRR is the best predictor of fire danger[3]. Research shows that compared to open-air experiments, HRR in tunnels can increase up to four times, making it more hazardous[4]. Current methods for analyzing tunnel fire scenarios, including numerical simulations, typically require data on the fire HRR. For instance, Lu H et al. studied the effect of tunnel fire HRR on the smoke exhaust efficiency of tunnel shafts and proposed an empirical model[5]. Youbo H et al. proposed a correlation model between the HRR and the temperature distribution of the tunnel ceiling in a tunnel with closed entrance[6]. Wang H Y utilized computational fluid dynamics (CFD) simulations to qualitatively establish the relationship between fire HRR and the dispersion of smoke and the generation rate of combustion products in tunnels[7]. Experiments conducted on-site or through modeling of tunnel fires indirectly estimate the HRR by observing the rate of combustible material loss or the generation of combustion byproducts. However, it can be challenging for firefighters to accurately assess the internal conditions within a tunnel in practice. The assessment of the fire situation is limited to observations of smoke at the tunnel entrances and exits, thereby hindering the precise evaluation of the fire's origin and progression.

To achieve a more accurate assessment of HRR, researchers have suggested employing neural network techniques for real-time HRR prediction. For example, Deng et al. used a multi-layer feedforward neural network to calculate and predict the HRR of different materials which shown a good performance[8]. Shu et al. utilized flame videos from propane combustion experiments to create a dataset. They developed a "flame volume/height - HRR prediction model" employing a support vector machine classifier. This model is capable of determining the fire HRR corresponding to flame volume or height data in a matter of seconds[9] . Wang et al. extracted 112 fire tests from the NIST fire database and trained a deep neural network with 69,662 fire scene images. The findings indicated that the model could identify transient fire HRR based on only the fire images, unaffected by the image backgrounds, camera settings, or angles[10].

The previous study has demonstrated that machine learning techniques have the potential to identify the attributes of fire HRR by leveraging extensive datasets, facilitating the swift collection of pertinent information in practical situations. In order to provide on-site information and a decision-making basis for fire warnings, this article proposes a method for using Informer neural networks to predict the subsequent development of HRR based on the inversion value of longitudinal temperature detector signals collected in tunnel sites.

2 Data Source and Data Processing

2.1 Full-size on-site testing

The experimental data in this study is derived from full-scale fire tests conducted in the Yunnan Baimang Snow Mountain Tunnel and the Shanghai Beiheng Passage[11-15]. Both tests used a pool fire as the ignition source, with a square fuel pool placed at the centerline of the tunnel as the fire source. Fiber optic grating sensors were installed below the centerline of the tunnel cross-section to record the temperature of the tunnel ceiling during the fire. The HRR rate was calculated using the mass loss method during the tests, with the calculation formula as follows:

$$Q = m'_{fire} \Delta H_c A_f \tag{1}$$

where Q is the HRR of the fire source (MW), m'_{fire} is the mass loss rate per unit area of the fire source (kg/(m$^2 \cdot$ s)), ΔH_c is the heat of combustion of the fuel (kJ/kg), and A_f is the area of the fire source (m^2). By changing the HRR of the fire source, ventilation airflow velocity, number of fire source points and other experimental conditions, simulations of multiple fire scenarios were conducted, and the readings of fiber optic grating sensors and the rate of mass loss in the fuel pool for each scenario were recorded as experimental data. The basic parameters during the on-site fire tests are shown in Table 1. Other specific experimental details and on-site conditions could be found in relevant literature[11-15].

Table 1. On-site fire test basic parameters.

Tunnel Name	Length(m)	Dimensions(m)	Slope(%)	Fuel Pool Size	Fuel Type	Burning Heat(kJ/kg)
Baimang Snow Mountain Tunnel	5180	6.85×10	0.6	0.8×0.8×0.1	Diesel	43000
Beiheng Passage	19100	10.5×4.4	0.5	0.8×0.8×0.1	Diesel	43000

2.2 Numerical Simulation Experiment

The constraints of test conditions prevent the acquisition of a substantial volume of data required for the training of neural networks via on-site testing. Hence, numerical simulation was employed to increase the quantity of data available. The FDS software was utilized to create computational models of the Baimang Snow Mountain Tunnel and Beiheng Passage[16]. The temperature sensor positions in the simulation tunnel model were set to be consistent with the on-site test. During fire simulations, the quadratic curve t^2 fire was applied to represent the HRR during the growth and steady stages of tunnel fires, with the calculation formula as follows:

$$\dot{Q} = \begin{cases} \alpha_{peak} t^2 & t \le t_{\max} \\ \dot{Q}_{\max} & t > t_{\max} \end{cases} \tag{2}$$

Numerical models were established in the FDS software based on the actual geometric dimensions and scale of the tunnel. By comparing the results of the numerical model calculations with the full-scale tunnel fire test results, the independence of the model grid size was analyzed. This analysis aimed to validate the numerical model's ability to accurately represent authentic fire conditions. The preset scenarios included in the numerical simulation are shown in Table 2. After the calculations were completed, temperature sensor and HRR data files for the entire simulation process were exported, serving as a supplement to the experimental datasets[15].

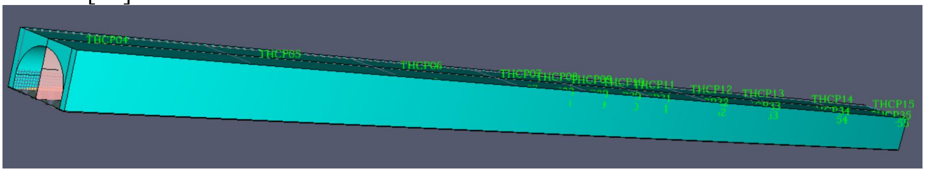

Fig. 1. Baimang Snow Mountain Tunnel numerical simulation model.

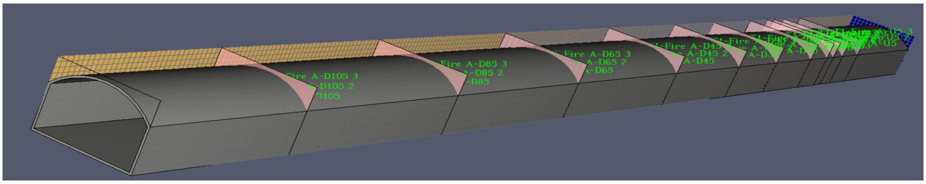

Fig. 2. Beiheng Passage numerical simulation model.

Table 2. Numerical simulation fire scenes.

Tunnel Name	Duration (s)	Peak HRR(MW)	HRR Increasing Rate	Ventilation Wind Speed(m/s)	Distance Between Fire Sources(m)	Number of Fire Scenarios
Baimang Snow Mountain Tunnel	600	0.5,1,1.5,2,2.5,3,3.5,4,4.5,5	very fast,fast,medium speed	0,1,2,3	/	26
Beiheng Passage	200	0.5,1,2,3,4	very fast,fast	0,1,2	5,10,20	38（single/double fire sources）

2.3 Data processing

Clean the datasets to eliminate noise by removing obviously incorrect data, for example, data rows with negative temperature or HRR values. Then normalize the data to map the results to the range of [0,1], so as to speed up the gradient descent of deep neural networks and improve model training efficiency. The normalization formula is as follows:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

where X_{norm} is the original data, $X_{\max}$ and $X_{\min}$ are the maximum and minimum values. This ultimately formed the experimental datasets for predicting the HRR in tunnel fire scenarios, which are composed of temperature sensor data from 12 key positions and HRR values. The Baimang Snow Mountain Tunnel Fire Dataset has 28,028 data points. The Beiheng Passage Fire Datasets have 14,014 single fire source data points and 26,026 double fire source data points. The study incorporates numerical simulations of temperature and HRR across diverse experimental fire scenarios, alongside actual on-site test measurements.

The datasets were segregated into training, validation, and test subsets according to their sources. The training and validation subsets were derived from numerical simulations, whereas the test subset comprises data from physical fire tests. In total, the training set contains 56,056 data points, the validation set contains 8008 data points, and the test set contains 4,004 data points.

3 Experiment content

3.1 Informer model

The Informer model is an innovative approach to time series forecasting that leverages a self-attention mechanism. Initially introduced at the AAAI 2021 conference, Informer is founded on the principles of self-attention and an encoder-decoder architecture[17]. The encoder component is designed to process extended sequences of raw data, facilitating the identification of temporal dependencies within the sequence via a multi-head probabilistic sparse attention mechanism. The decoder then generates predictions for time series by interacting with encoding features. Expanding upon the Transformer model, the Informer incorporates a sparse self-attention mechanism instead of conventional attention mechanisms. The computational framework of the Informer model can be succinctly articulated as follows:

$$attention(\hat{Q}, K, V) = Softmax(\frac{\hat{Q}K^{T}}{\sqrt{d}})V \tag{4}$$

where $\hat{Q}$ is the query vector determined based on the importance of the query point after calculating the KL divergence between the attention distribution and the uniform distribution. K serves as the key vector, V as the value vector, and d as the input dimension. Compared to the quadratic time complexity of traditional self-attention mechanisms, probabilistic sparse self-attention reduces the time complexity to $O(LlnL)$.

The Informer model employs distillation techniques within the encoder to prioritize the analysis of sequences containing prominent features, consequently diminishing input dimensions and effectively managing lengthier input sequences. The distillation mechanism, which occurs progressively from one layer to the next, is mathematically represented by the following equation:

$$X_{i+1}^{t} = Maxpool(ELU(Conv1d([X_i^t]_{AB}))) \tag{5}$$

where $[X_i^t]_{AB}$ is the attention block containing multi-head self-attention. $Conv1d$ is used for convolution operations. ELU is the activation functions, and $Maxpool$ is the pooling operations. After distillation, the feature representation of the input sequence is halved at each layer, thereby reducing the memory usage.

Generative reasoning was facilitated through the utilization of two multi-head attention layers and a feedforward neural network to produce the prediction outcomes. One of the attention layers employed was a multi-head probabilistic sparse self-attention layer with occlusion, aimed at covering future time period data to mitigate the model's autoregression. The input vector of this layer can be represented as described below:

$$X_{feed\_dec} = Concat(X_{token}, X_{placeholder}) \in R^{(L_{token}+L_y)\times d} \tag{5}$$

where X_{feed_dec} represents the input sequence of the decoder. X_{token} represents the known historical sequence. $X_{placeholder}$ is the zero-filled sequence to be predicted. L_{token} is the length of the known historical sequence and L_y is the length of the sequence to be predicted. The operation principle of Informer is shown in Figure 3 below[17].

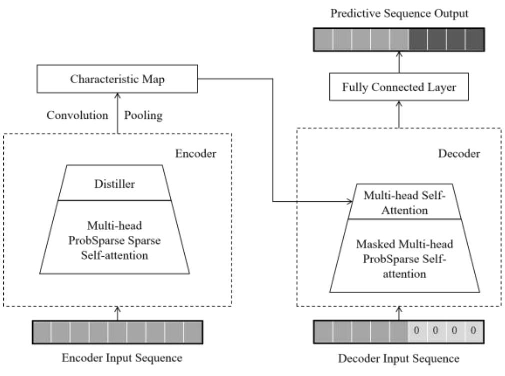

Fig. 3. Schematic diagram of Informer operation principle.

3.2 Informer model

The study utilized Windows 10 Professional Edition as the experimental operating system, with the Informer model environment constructed through the Python PyTorch library. The system features an AMD Ryzen 7 5800H processor, NVIDIA GeForce RTX 3060 GPU, and 32GB DDR4 RAM. The specific hyperparameters employed in the experiment are detailed in the table below, with default values assumed for any parameters not explicitly specified.

Table 2. Numerical simulation fire scenes.

Hyperparameter Name	Hyperparameter Meaning	Hyperparameter Value
e_layers	encoder layers	2
d_layers	decoder layers	1
d_model	model dimension	512
d_ff	full convolutional layer dimension	2048
n_heads	number of self-attention heads	8
batch_size	batch size	32
learning_rate	learning rate	0.0005
seq_len	encoder input sequence length	96
label_len	decoder sequence length	48

3.3 Experiment evaluation index

The evaluation indexes selected in this experiment are Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2), and the calculation formulas are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \tag{8}$$

Where, y_i represents the true value of the HRR, $\hat{y}_i$ represents the predicted value of the HRR, $\overline{y}_i$ represents the average of the true value of the HRR and n represents the length of the test data. The lower the value of $RMSE$ and MAE, and the closer the value of R^2 is to 1, the better the prediction performance of the model is.

4 Experiment result

4.1 Prediction results of multiple scenarios

Figure 4-6 shows the prediction results obtained by Informer model in the test datasets of Baimang Snow Mountain Tunnel and Beiheng Passage respectively. The Beiheng Passage results are divided into two working conditions of single fire source and double fire sources. The number of time steps predicted by the model is 24, and the time step size corresponding to the data of Baimang Snow Mountain is 0.6 s, while Beiheng Passage is 0.2 s.

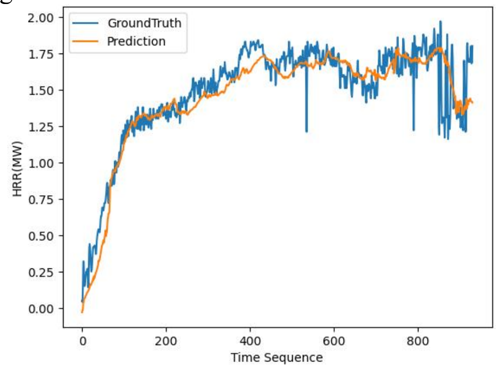

Fig. 4. Prediction results of fire HRR in Baimang Snow Mountain Tunnel.

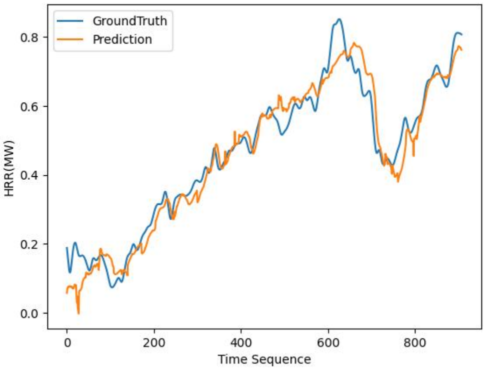

Fig. 5. Prediction result of fire HRR in the Beiheng Passage(single fire source).

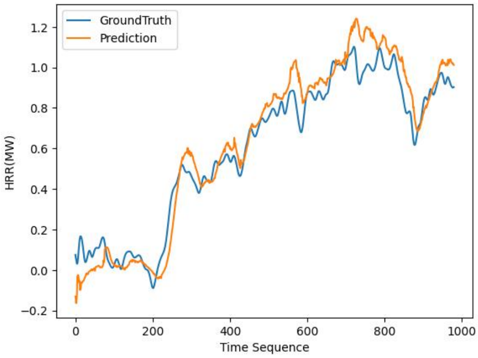

Fig. 6. Prediction result of fire HRR in the Beiheng Passage(double fire sources).

Table 3. Prediction results of HRR on tunnel fire datatests

Name of the Dataset	Number of Predict Time Steps	Time Interval Length(s)	RMSE	MAE	R^2
Baimang Snow Mountain Tunnel	24	14.4	0.134	0.102	0.87
Beiheng Passage(single fire source)	24	4.8	0.111	0.080	0.94
Beiheng Passage(double fire sources)	24	4.8	0.181	0.115	0.92

The findings from Figure 4-6 and Table 4 indicate that the Informer model effectively captures the variations in the HRR during the growth and stabilization stages of tunnel fires. The model's predictions align with the observed trends in the experimental data, proving its ability to accurately represent the changing dynamics of HRR in tunnel fire scenarios. The model has demonstrated strong predictive performance across various tunnel types and fire conditions, particularly excelling in the single fire source test dataset of the Beiheng passage where it achieved a high value of 0.94, indicating a high level of prediction accuracy. Upon completion of the model training process, the prediction time is less than 1 second, thereby satisfying the need for a quick response. However, the predicted value of the HRR in the initial stage of the fire in the Beiheng Passage experiment is negative, which may be resulted from the fact that the data in the training set are continuously connected from the fire stability stage of the previous fire condition to the initial stage of the next fire condition, leading to a misjudgment of the decreasing amplitude of the HRR value.

4.2 Prediction results of different time steps in a single scene

By changing the number of predicted time steps to 48 and 96, the model was retrained using the same datasets. The experimental results were obtained as shown in the following table.

Table 4. Prediction results of fire HRR in Baimang Snow Tunnel at different time steps

Name of the Dataset	Number of Predict Time Steps	Time Interval Length(s)	RMSE	MAE	R^2
Baimang Snow Mountain Tunnel	24	14.4	0.134	0.102	0.87
	48	28.8	0.159	0.127	0.81
	96	57.6	0.194	0.148	0.74
Beiheng Passage(single fire source)	24	4.8	0.111	0.080	0.94
	48	9.6	0.113	0.081	0.91
	96	19.2	0.156	0.111	0.79
Beiheng Passage(double fire sources)	24	4.8	0.130	0.079	0.92
	48	9.6	0.179	0.115	0.85
	96	19.2	0.249	0.171	0.81

The outcomes presented in Table 5 demonstrate a notable impact of the number of time steps on the predictive performance of the Informer model. Specifically, an increase in the number of prediction steps correlates with a decrease in the accuracy of prediction results. In the test prediction results of Baimang Snow Tunnel, compared with the prediction of 24 steps, the values of with 48 and 96 steps decreased by 6.9% and 14.9% respectively. In addition, in the results of the Beiheng Passage Tunnel, it can be observed that compared to the 24-step forecast, the predictions for single-fire and double-fire scenarios at 96 steps decreased by 16% and 12%, respectively. This indicates that when utilizing the Informer model, it is advisable to avoid predicting over extended time horizons, as doing so may result in predictions that do not align well with reality.

It is worth noting that the determination of HRR in this study is achieved through either the mass loss method or direct input in numerical simulations. In cases where obtaining precise HRR values during actual tunnel fire faces challenges, regression analysis can be utilized to estimate HRR by gathering temperature sensor data beforehand, enabling subsequent predictive analyses[14].

5 Summary

This study proposes a novel method for using the Informer neural network model to predict subsequent HRR, building upon the determination of HRR through regression analysis or other way. This method is validated through experimental investigations utilizing numerical simulations and on-site test data of tunnel fires. After training, the model can provide HRR prediction results for the next few seconds within only one second while maintaining high accuracy. The findings demonstrate that this method offers accurate short-term HRR predictions and rapid response capabilities, meeting the requirements of on-site sudden fire incident response. In the future, the applicability and predict length of this model can be further improved by establishing a larger dataset which contains more tunnel type and fire scenarios.

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