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Real-time detection and temperature forecasting of large-space building fires using machine learning

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Abstract

In firefighting, timely knowledge of fire behavior is essential but often lacking. This study integrates building design and recorded gas temperatures to determine fire conditions and forecast temperature changes, employing a machine learning system that merges long short-term memory (LSTM) networks with transfer learning. The model is initially trained on datasets comprising 1000 samples from parametric fire models and 200 samples from field simulations, facilitating real-time predictions based on on-site data. Simulations in portal frame buildings show the model achieves over 95% accuracy in fire detection and 90% in gas temperature forecasting. A technique using correlation coefficients and standard deviations effectively identifies damaged thermocouples with over 96% accuracy, assuming a damage ratio under 30%. Validation in two real fire incidents demonstrated over 92% accuracy in fire location and over 89% accuracy in predicting gas temperatures 20 minutes ahead, with processing times of 2.14 seconds and 1.83 seconds, respectively. The machine learning framework also proves resilient to variations in ventilation conditions, making temperature predictions using reliability theory. This framework provides critical insights into fire status and progression for firefighters, contributing to advanced firefighting strategies.

Keywords: Advanced firefighting; Fire detection; Temperature forecasting; Machine learning; Transfer learning

1. Introduction

Building fires pose severe risks to both human lives and property, causing extensive damage through intense heat and smoke. Ensuring fire safety is a critical concern throughout the design and lifecycle of buildings. Research efforts have focused on minimizing fire risks by proposing regulations for fire prevention (Spinardi, 2016) and developing automated detection or suppression systems for early-stage fires (Ahn et al., 2023; Cheng et al., 2017). Other studies have aimed to enhance fire resistance in buildings by applying fire-resistant coatings (Akaa et al., 2016; Gernay et al., 2023) or optimizing structural designs (Gehandler, 2017; Gernay & Khorasani, 2020). Despite these advancements, uncontrolled building fires still occur due to human errors or environmental factors, causing significant damage, particularly in large-space buildings where automatic fire detection and suppression systems are less effective (Chen et al., 2004). Additionally, fires in large-space buildings can lead to catastrophic structural collapses, which have substantial social and economic repercussions, especially given that such buildings often accommodate large numbers of people or store substantial amounts of materials. Therefore, addressing fire emergencies in large-span buildings remains a crucial issue for firefighters.

Accurate assessment of fire conditions and reliable predictions of fire development are essential for effective decision-making and improved firefighting efficiency (Guyo et al., 2023). Traditionally, firefighters estimate fire locations using pre-installed sensors and signal processing algorithms, but accurately determining the heat release rate (HRR) is challenging due to the complex relationship between HRR and sensor data. Consequently, firefighters often rely on

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visual assessments, which can be imprecise, especially in complex structures like large-span buildings. Some researchers have used inverse fire modeling techniques to estimate fire severity (Overholt & Ezekoye, 2012; Richards et al., 1997), reverse-calculating HRR from hypothetical equations until the temperature matches expected values. For fire development predictions, classical fire models and computational fluid dynamics (CFD) models are used to predict gas temperatures, but they often have limited lead times and handling durations, which may not meet the urgent needs of fire rescue operations (Shen et al., 2008; Yan & Gernay, 2021).

With advancements in the Internet of Things (IoT) and machine learning (ML), smart firefighting has emerged as a significant research area (Khan et al., 2022). This approach enables early fire detection (Baek et al., 2023; Yar et al., 2023), enhances city fire resilience (Alonso-Betanzos et al., 2003; Zhang et al., 2021), automates escape route planning (Shih & Tsai, 2023; Wagner & Agrawal, 2014), and speeds up information transmission during emergencies (Wong & Lee, 2022; 2023). For intelligent decision-making in fire scenarios, Jaber et al. (2001) introduced Telegeoprocessing and Intelligent Software techniques for forest firefighting. Wu et al. (2022) and Zhang, Xu, and Huang (2022) developed AI-based systems for tunnel fires that provide real-time temperature data and forecast fire development 30 seconds in advance based on embedded thermocouples.

Recent studies in machine learning for fire identification and prediction, as summarized in Table 1, mainly concentrate on assessing fire characteristics such as location, heat release rate, and temperature using data from temperature measurements, imagery, or smoke detection. This approach aids firefighters in real-time assessment and decision-making. However, predicting fire progression remains less explored, with limited studies on forecasting critical events like flashovers, offering minimal lead time for planning. Fire prediction is challenging due to the unpredictable nature of combustion dynamics and varying environmental conditions, and model accuracy tends to decrease with longer forecast periods. Improving long-term fire development predictions, despite these challenges, is a key objective of this paper.

Building fires are generally categorized into compartment fires and large-space fires, with most research focusing on the former. Compartment fires, common in residential or office buildings, can lead to flashover, where hot gases fill the entire space, causing uniform gas temperatures. In contrast, large-space fires do not lead to flashover, resulting in uneven gas temperature distribution. This difference in fire behavior highlights the need for dedicated research on large-space fires.

There is a significant gap in research on the smart identification and prediction of fires in large spaces, which are critical due to their size and occupancy. This paper addresses this gap by developing methods for the identification and long-term prediction of fires in large buildings. Unlike traditional methods, the ML model offers real-time results after offline training, effectively addressing urgent practical challenges. A key issue in using ML techniques is obtaining sufficient training data that accurately reflects real-world conditions. To tackle this, Saida and Nishio (2023) used transfer learning to reduce the computational load of structural reliability analysis with a Gaussian process regression model. Li, Zhang, et al. (2022) developed an online transfer learning-based method to address sample insufficiency in optimization tasks. Rashid and Louis (2019) proposed a data-augmentation framework for generating synthetic training data in construction sites, while Parida et al. (2023) used singular value decomposition to extend training data for the dynamic response of civil structures. These approaches advance the application of ML methods in fire safety engineering despite the limited availability of real fire data.

This study proposes an ML model for real-time fire parameter identification and temperature forecasting in large-space building fires using recurrent neural networks (RNNs) and transfer learning. The paper is organized as follows: Section 2 describes the ML framework, including the transfer learning strategy, network architecture, and parameter update procedure. Section 3 demonstrates the ML framework through fire cases in steel portal frames, evaluating the performance of the trained model and discussing the role of transfer learning. Section 4 validates the trained model's robustness through natural fire tests. Section 5 examines the model's resilience by considering damaged thermocouples and changes in ventilation conditions during real fires.

2. ML Framework

2.1. Research Objective

Effective identification of fire conditions and prediction of fire progression are crucial aspects of smart firefighting, aiding firefighters in obtaining precise information about a fire and making informed decisions. Existing research predominantly addresses compartment fires, where gas temperatures are generally considered uniform following flashover. Additionally, most fire prediction studies offer lead times of less than one minute due to the inherent uncertainties in fire behavior. This paper seeks to address these issues by focusing on large-space fires, where gas temperatures are distributed unevenly throughout the burning area. The goal is to develop methods for real-time identification of fire location and heat release rate, as well as to make long-term predictions of gas temperature evolution in large-space fires, thereby facilitating more effective firefighting in these scenarios.

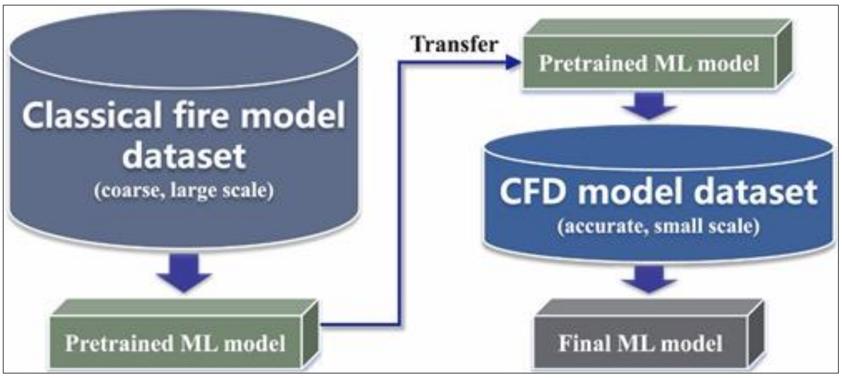

Figure 1 Research Objective

2.2. Method Description

The distribution of gas temperatures in a large-space fire is influenced by various fire parameters such as the size of the fire and the heat release rate, as well as structural factors like building dimensions and ventilation conditions. During the design phase, different combinations of these parameters are analyzed to assess the building's thermal response in potential fire scenarios and to adjust fire safety measures accordingly. However, once a building is on fire, many of these parameters are unknown, particularly fire-related ones, creating challenges for firefighters in assessing fire severity and predicting its development. This paper proposes a method leveraging historical temperature data from pre-installed thermocouples to infer fire conditions and forecast fire progression. To address the urgent nature of fire emergencies, the study introduces a machine learning (ML) model that can rapidly and accurately identify fire parameters and predict gas temperatures once it has been adequately trained. The model uses historical gas temperature data and building geometry as inputs, producing fire parameters and future temperature predictions as outputs. This ML model can be trained offline prior to an incident and applied in real-time during a fire.

2.3. Transfer Learning

An essential requirement for training an accurate ML model is the availability of sufficient sample data. However, obtaining real fire data for buildings that are not currently on fire is nearly impossible, and conducting scaled fire tests to collect training data is both complex and costly. Classical fire models provide simplified representations of temperature field dynamics during combustion and propose general calculation methods based on specific assumptions. While data from these models can be readily obtained, discrepancies between the model assumptions and actual fire conditions can impact dataset accuracy. On the other hand, computational fluid dynamics (CFD) models, such as the Fire Dynamics Simulator (FDS), offer precise temperature field computations based on complex fluid dynamics analyses, validated against real fire tests. However, CFD models involve high computational costs.

To address these challenges, a transfer learning approach is proposed, as illustrated in Fig. 1. Initially, the ML model is trained on a large, coarse dataset generated by classical fire models to learn simplified relationships between fire parameters and gas temperatures. Following this, the model is further trained on a smaller, more refined dataset from FDS models to capture more accurate relationships. After the initial training, certain layers of the model are "frozen," meaning their parameters remain fixed in subsequent training phases. The pre-trained model is then fine-tuned using the FDS dataset, with updates made only to the parameters of the unfrozen layers.

The length of the input time-series data is denoted as Δt1\Delta t_1Δt1, while Δt2\Delta t_2Δt2 represents the length of the output time-series data. The batch size used for each training iteration is indicated by nbnbnb, and these hyperparameters must be adjusted based on the performance of the training process. In Fig. 2, ⊕\oplus⊕ signifies element-wise addition between two matrices, and only the outputs from the final sequence of Layer 2 are utilized in mathematical operations with the outputs from Layer 3 to maintain dimensional consistency.

During model training, ttt represents the duration of the training sample and is typically a fixed value. However, in practical scenarios, ttt corresponds to the duration of the fire, which extends as additional measurements are taken.

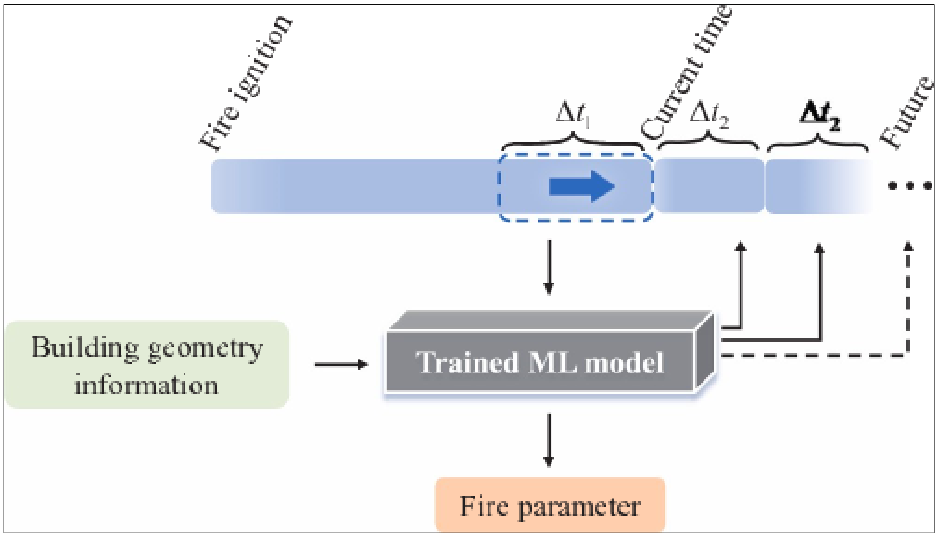

Figure 2 Learning Model

2.4. Loss Function

To enhance the neural network's performance, the model updates its parameters during training by minimizing the loss function. The choice of loss function plays a critical role in influencing the ML model's behavior. This study employs two distinct loss functions for two different types of outputs.

In contrast to fire parameter identification, which deals with known fire scenarios, fire development prediction involves forecasting unpredictable events with inherent uncertainties. Thus, Quantile Loss (QL) functions are used in fire prediction to provide predictions with a specified confidence level (Zhang, Watkins, & Kuenzel, 2022). The QL function is computed as:

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3. Numerical Example

3.1. Geometric and Fire Parameters

To illustrate the application and effectiveness of the ML model, we examined fires in single-span steel portal frames, as shown in Fig. 4. The geometric characteristics of the steel portal frames, detailed in Table 2, were modeled as discrete random variables with a uniform distribution. This approach allows the ML model to adapt to frames of various sizes.

In contrast to geometric parameters, fire parameters such as the fire location and intensity are not known in real-time during a fire. These parameters must be inferred by the ML model from measured temperatures. Consequently, they were treated as random variables during model training based on the following guidelines:

Fire Location Parameters A rectangular coordinate system was established within the steel portal frames, as depicted in Fig. 4. To maintain consistency across different frame sizes, the plane dimensions of the frame were normalized to the interval [−1,1][-1, 1][−1,1], thereby removing the effect of varying geometric dimensions. The initial relative position of the fire center, denoted as L0xL_0^xL0x and L0yL_0^yL0y, was assumed to follow a uniform distribution, as outlined in Table 3, where NNN represents the number of bays.

Fire Intensity Parameters The fire area was modeled as a simplified square plane with an initial side length D0D_0D0 and a constant heat release rate per unit area, denoted as Q0Q_0Q0. The side length of the fire area expands at a constant velocity vdv_dvd until it reaches a maximum size at time tdt_dtd. The fire intensity at any time ttt is determined by the total heat release rate Q(t)Q(t)Q(t), calculated as: Q(t)=Q0·A(t)Q(t) = Q_0 \cdot A(t)Q(t)=Q0·A(t) where A(t)A(t)A(t) is the fire area, given by:

3.2. Input and Output of ML Model

The ML model utilizes two primary types of inputs: geometric parameters and historical gas temperature data.

- **Geometry Parameters**: The geometry parameters of a steel portal frame, which are fixed post-construction and obtainable from design documents, are used as inputs. These parameters are time-independent and are represented as: g={S,C,H,N}g = \{S, C, H, N\}g={S,C,H,N} where SSS, CCC, HHH, and NNN are defined in Table 2.
- **Gas Temperature Data**: Historical gas temperatures are collected by thermocouples embedded in each bay of the steel portal frames, as depicted in Fig. 5. With a total of 6×N6 \times N6×N thermocouples (where NNN is the number of bays), the dimension of the temperature input is linked to the number of bays. To standardize the model for frames with any number of bays, data from the five most affected bays are selected based on the following rules:
- **Outputs**: The ML model outputs several fire parameters, including the locations of fire centers and the heat release rate, which provide firefighters with critical information about fire locations and intensity. The fire parameters are normalized to [−1,1][-1, 1][−1,1] to account for varying geometry dimensions, and the square root operation is applied to the heat release rate QQQ to reduce output variation. The fire output at the tttth An example of the ML model's inputs and outputs at the tttth time step is illustrated in Fig. 6.

3.2.1. Validation and Modification of Classical Fire Models

To validate and refine classical fire models, two fire scenarios were simulated using the Fire Dynamics Simulator (FDS), and their results were compared with those from classical fire models. The geometry and fire parameters for these scenarios are detailed in Table 5.

Fire Case Simulation

The FDS simulations utilized the fire spread option, where the fire started from an initial point and spread circularly at a rate vrv_rvr until reaching predefined boundaries. The gas temperatures from these simulations were compared with those calculated using classical fire models, including the Zukoski, McCaffery, and NFPA models. The comparison results are illustrated in Fig. 8, with F, Z, M, and N denoting temperatures from FDS, Zukoski model, McCaffery model, and NFPA model, respectively.

Results and Adjustments

From Fig. 8, it is evident that:

- Thermocouples near the fire plume centerline (e.g., T3) showed good agreement between FDS and various fire plume models.
- Significant discrepancies were observed for thermocouples T1 and T5 when using the ceiling jet flow model and large space model compared to FDS simulations.

The ceiling jet flow model, which describes temperature distribution below an unconfined ceiling, was found to be inadequate for building fires due to wall constraints, which restrict hot air diffusion. This discrepancy led to higher actual temperatures than predicted by the unconfined ceiling model. To address this, the coefficients of the ceiling jet flow model for strong-plume flow were adjusted for building fires, as detailed in Eq. (29).

Additionally, the simulation demonstrated that hot air diffuses downward along walls, contributing to the gas temperature near columns through two mechanisms:

- Hot air moves from the ceiling to the wall.
- Hot air moves directly from the fire centerline to the wall.

This dual heat transfer mechanism was accounted for in the revised temperature calculation for gas temperatures near columns. The modified fire models, which incorporated these adjustments, showed results closer to FDS simulations, as seen in Fig. 10.

3.2.2. Model Training

To train the ML model, a dataset consisting of 5000 samples was generated using classical fire models with randomly distributed geometry and fire parameters. The dataset was divided into three subsets:

- **Training Subset:** 3000 samples
- **Validation Subset:** 1000 samples
- **Test Subset:** 1000 samples

The training and validation subsets were used for model pre-training to adjust the network parameters, while the test subset served as an entirely new dataset for evaluating the performance of the pre-trained model.

Training Details

- **Hidden Layer Size:** 20 units
- **Heating Duration per Sample:** 60 minutes
- **Input and Output Window Sizes (Δt1\Delta t1Δt1 and Δt2\Delta t2Δt2)**: Both set to 5 minutes

This setup allows extraction of 51 input-output sample pairs from each training sample, leading to a total of 153,000 training pairs. A large batch size of 512 was chosen to optimize training time, meaning that each epoch involved updating network parameters using 512 randomly selected samples from the training dataset.

Training Procedure

- **Framework:** TensorFlow in Python
- **Maximum Epochs:** 5000
- **Early Stopping Criteria:** Training halts if the validation loss does not decrease by more than 0.0001 over 300 epochs.

Initialization:

- **Weights:** Xavier uniform initialization
- **Biases:** Initialized to zero

Scaling:

Inputs and outputs were scaled to the range [−1, 1] to improve model performance.

Confidence Levels (τ\tauτ): 5%, 50%, 80%, and 90% **Weight Hyperparameter (α\alphaα):** 0.2

- **Training Hardware**
- **CPU:** Intel® Core™ i7-12700K @ 3.60 GHz
- **GPU:** NVIDIA GeForce RTX 4090

Model Evaluation: The model with the lowest validation error during training was selected as the best-performing model. Fig. 11 shows the history of the loss functions on a logarithmic scale throughout the training process.

This comprehensive training approach ensures robust model performance for predicting fire parameters and gas temperatures in large-space fires.

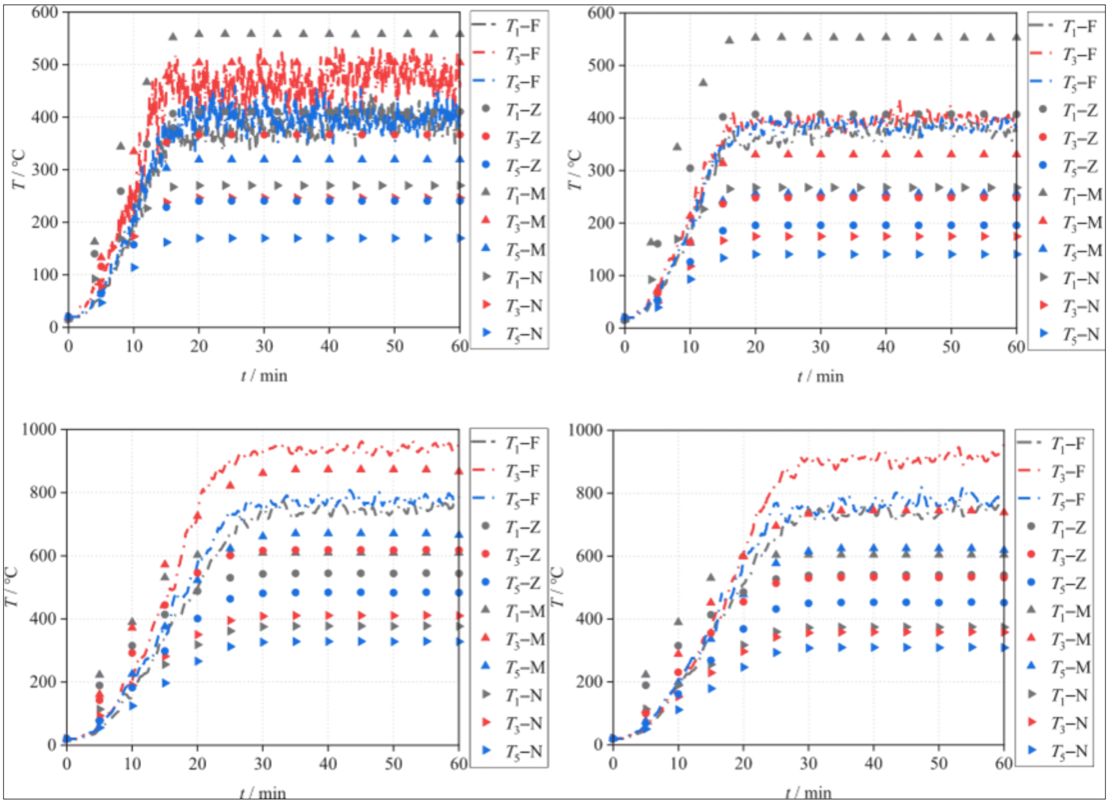

Figure 3 Model Training (A)

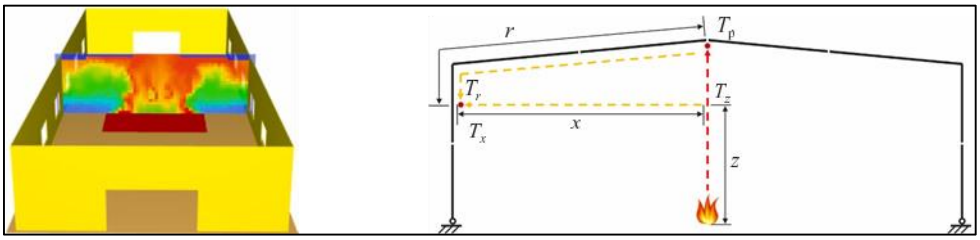

Figure 4 Model Training (B)

3.3. Transfer Learning Model

3.3.1. Model Training

For the transfer learning phase, a dataset of 50 samples was generated using FDS with randomly assigned geometry and fire parameters. This dataset was divided into three subsets:

- **Training Subset:** 30 samples
- **Validation Subset:** 10 samples
- **Test Subset:** 10 samples
- **Pre-Simulation Checks:** All FDS models were verified to ensure they met the following criteria:
    - Geometry dimensions aligned with Chinese codes
    - The burning area was within the building boundaries
    - The heat release rate did not exceed the maximum allowed for industrial buildings

Data Preparation

- **Gaussian Smoothing:** Applied to the simulated gas temperatures before including them in the dataset.
- **Data Augmentation:** Involved mirroring the fire along the x-axis, y-axis, and O-point, and exchanging

temperature data at corresponding positions. This process expanded the dataset to:

- **Training Subset:** 120 samples
- **Validation Subset:** 40 samples
- **Test Subset:** 40 samples

With the same heating duration and window sizes as the pre-training phase, this augmentation resulted in 6120 training pairs. A smaller batch size of 64 was used to fit the augmented dataset.

Transfer Learning Process

- **Framework:** TensorFlow in Python
- **Hardware:** Same server as used in the pre-training phase
- **Scaler Settings:** Same scaling settings as in pre-training
- **Epochs:** Maximum of 5000
- **Early Stopping:** Same criteria as pre-training

Model Adaptation

- **Base Model:** The best model from pre-training was used for transfer learning.
- **Layer Adjustment:** Only layers 4 and 10 were updated, while others were frozen. These layers were selected after multiple trials and errors. A smaller learning rate (η=0.0001\eta = 0.0001η=0.0001) was applied to refine network parameters with more precision.
- **Results:** The history of loss functions during transfer learning is depicted in Fig. 12. This phase effectively enhanced the model's performance by leveraging the pre-trained knowledge and fine-tuning specific layers to better adapt to new data.

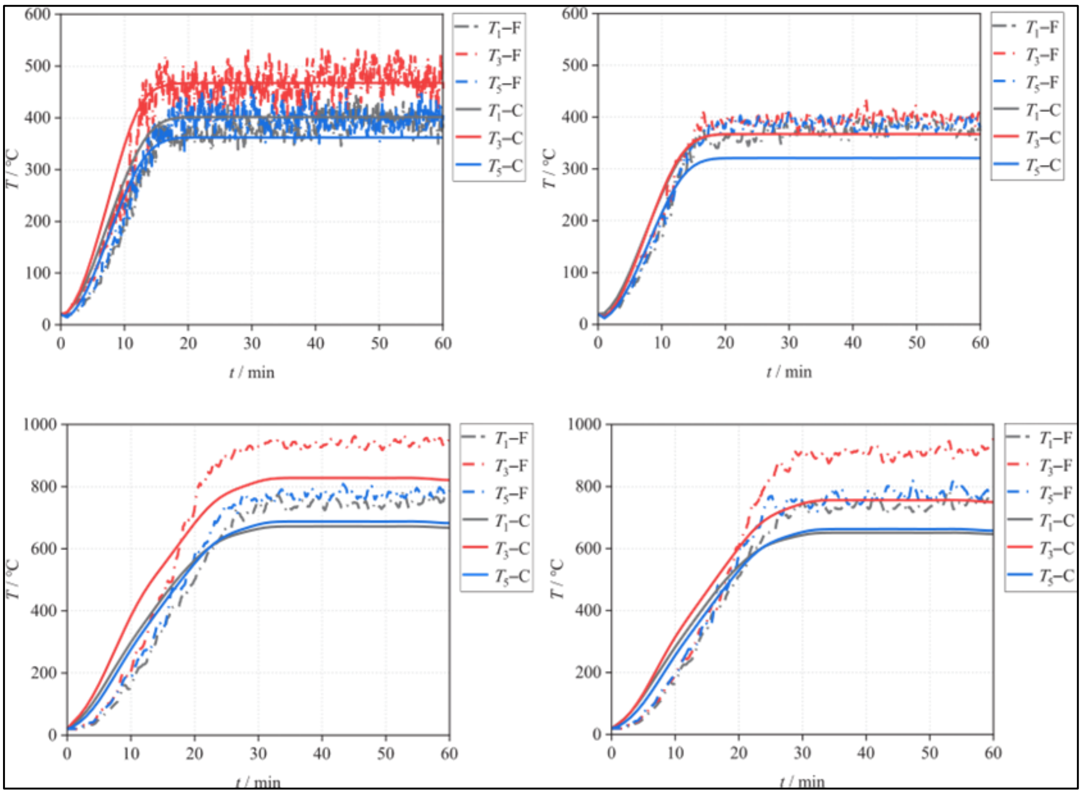

Figure 5 Model Training (C)

3.3.2. Model Performance

After the transfer learning phase, the performance of the model was evaluated using the FDS test subset. The evaluation was conducted at various fire exposure times: 10 min, 15 min, 20 min, 25 min, 30 min, 35 min, and 40 min.

Identification Accuracy:

- **Fire Locations Along the Span:** About 80%
- **Fire Locations Along the Column Spacing:** About 85%
- **Heat Release Rate:** About 60%

In approximately 90% of the cases, the model achieved these accuracy levels. The average identification accuracies for the test subset were:

- **Fire Locations:** 89.6%
- **Fire Intensity:** 91.8%
- **Heat Release Rate:** 79.8%

These results indicate that the trained model performed well in identifying fire parameters.

Temperature Prediction Performance

The evaluation index IWIWIW of the temperature prediction results was calculated for various fire exposure times. Fig. 14 shows the probability distribution of IWIWIW for the 20-minute prediction interval using box charts. The distribution of IWIWIW shifts from negative to positive intervals with increasing confidence level τ\tauτ, reflecting the reliability of the predictions.

- **Accuracy Indices:** The accuracy indices for the temperature predictions were calculated according to Eq. (16). Table 6 displays the average accuracy (ACACAC) of the test samples at different fire exposure times and prediction intervals. As the fire exposure time increases, the gas temperature stabilizes, which enhances prediction accuracy. However, with longer prediction intervals, the accuracy decreases due to the less representativeness of current data for future fire states.
- Despite this decrease, the model maintained an average prediction accuracy of 90% with a 20-minute prediction interval.
- **Summary:** The model demonstrated strong performance in identifying fire parameters and predicting future temperatures. It achieved high identification accuracies and maintained a good prediction accuracy even with extended time intervals, reflecting its reliability in practical fire scenarios.

3.3.3. Necessity of Transfer Learning

To assess the need for transfer learning, the performance of the pre-trained agent from Section 3.4.2 (without transfer learning) was compared to the transfer-learned model. The FDS test dataset was used to evaluate the agent's performance on fire parameter identification and temperature prediction.

Performance Comparison:

- **Fire Parameter Identification:**
  - **Fire Locations:** The average identification accuracy decreased by approximately 10%.
  - **Heat Release Rate:** The identification accuracy dropped by over 50%.
- **Temperature Prediction:**

The prediction accuracy (denoted as TTT) decreased by approximately 5% for a 20-minute prediction interval.

Summary: The comparison shows that the pre-trained model, which was trained on a coarse fire dataset, underperforms in practical scenarios. The significant decrease in accuracy for both fire parameter identification and temperature prediction highlights the importance of transfer learning. Transfer learning effectively combines the detailed accuracy of the FDS dataset with the extensive training data from classical fire models, leading to improved performance. This demonstrates that incorporating transfer learning is crucial for enhancing model accuracy and practical usability.

3.4. Change in Ventilation Conditions

In real fires, high temperatures can damage windows and cause significant deformations to the roof of a burning frame, leading to changes in ventilation conditions. These changes can affect the combustion process and the flow of hot gases, which in turn influences the measured gas temperatures. The proposed ML network is designed to implicitly identify these changes in ventilation conditions and make predictions based on this information.

3.4.1. Experimental Setup

Simulation Framework

A burning frame is modeled in FDS, considering potential damage to windows and the roof. The frame's dimensions are 24 m span and 8 m eaves height, with 5 bays each 9 m apart. The fire starts in the middle and spreads circularly at 3 mm/s until it reaches predefined boundaries (Fig. 15).

Initially, all windows are closed but get damaged when temperatures exceed their thresholds. The ultimate temperatures and damage times of windows and the roof are documented in Table 8.

Data Collection

Gas temperatures measured at various fire exposure times are fed into the trained ML model to identify fire parameters and predict temperature changes under different ventilation conditions.

3.4.2. Results and Analysis

Fire Parameter Identification

The identification errors for fire center locations and heat release rates are assessed (Fig. 16). After 20 minutes, the absolute identification errors for fire locations reach 1 m due to changes in hot air movement caused by broken windows and roof, with maximum errors not exceeding 1 m and 3 m, respectively.

Identification accuracy for fire locations remains above 90% throughout the fire, which is sufficient for effective firefighting. However, the ML model's accuracy for estimating heat release rate drops to about 55% after 15 minutes due to altered ventilation conditions.

Temperature Prediction:

Predicted gas temperatures near damaged windows and the roof (denoted as T1T_1T1 and T2T_2T2) at different fire exposure times (10 min, 20 min, and 40 min) are analyzed (Fig. 17). The ML model effectively captures the impact of damaged windows on gas temperatures and can predict temperature changes under these conditions.

While the ML model can predict temperature development based on the identified fire state, it cannot predict the exact timing of window damage. As a result, prediction errors increase over time, especially as more windows are damaged.

Reliability Theory and Quantile Loss Function

The ML model incorporates reliability theory and uses a quantile loss function to handle uncertainties such as material combustion and ventilation changes. This approach allows the model to provide temperature predictions at specific confidence levels (Fig. 17).

The predicted temperature trends align with actual developments, indicating that the ML network effectively accounts for ventilation changes in its predictions.

Conclusion: The ML model demonstrates robustness in handling variations in ventilation conditions due to damage, providing reliable temperature predictions even as conditions change during a fire. The integration of reliability theory and the quantile loss function enhances the model's ability to account for uncertainties and deliver accurate predictions.

4. Experimental Validation and Case Study

4.1. Parametric Scheme of Hyperparameters and Network Layers of ML Model

4.1.1. Hyperparameter Tuning:

The weight hyperparameter α\alphaα defined in Eq. (4) plays a crucial role in balancing the ML model's performance between two types of outputs: fire state identification and gas temperature prediction.

A higher α\alphaα typically improves performance on fire state identification but may reduce accuracy in gas temperature prediction, and vice versa. Given the interconnected nature of these outputs in describing fire dynamics, selecting an appropriate α\alphaα is essential for optimizing overall model performance.

The ML models were tested with α\alphaα values of 0.4 and 0.6, using the same dataset and training process outlined in Section 3. Their performance was compared using fire test data described in Sections 5.2 and 5.3.

4.1.2. Model Comparison

Long Short-Term Memory Networks (LSTM) vs. Temporal Convolutional Networks (TCN):

To explore the effectiveness of LSTM in this context, a comparison is made with Temporal Convolutional Networks (TCNs). TCNs, as described by Zeng et al. (2024), are designed for sequence modeling and leverage hierarchical temporal convolutions to capture patterns over different time scales.

In the comparison, all LSTM layers (layer numbers 1, 2, 8, and 9) were replaced with TCN layers. The TCN layers used had 12 filters and a kernel size of 2, resulting in a total of 18,499 network parameters, similar to the original LSTM-based network.

The performance of the ML model with TCN layers was evaluated using the same fire test data presented in Sections 5.2 and 5.3 to ensure a fair comparison.

The following sections will present the results of these evaluations, focusing on the effectiveness of different hyperparameters and network architectures in predicting fire dynamics.

4.2. Reduced-Scale Fire Test

4.2.1. Test Setup

A real fire test was performed on a scaled-down steel portal frame (Li et al., 2021), as illustrated in Fig. 18(a). The frame, representing three bays of a real structure, was scaled to 1:4 for simplification. The dimensions were a span of 7 m, column spacing of 1.5 m, and an eaves height of 1.75 m.

Heptane was used as fuel, with two oil trays arranged along the span, and the fire location was centered on these trays, as shown in Fig. 18(b).

Gas temperatures near the heated columns and rafters were measured using thermocouples (Fig. 19).

4.2.2. Input Preparation for ML Model

The ML model requires the geometry dimensions and gas temperatures from the five most affected bays. For the test frame, the geometry input is inverse-scaled to match the real frame, resulting in g={28,6,7,5}g = \{28, 6, 7, 5\}g={28,6,7,5}.

The gas temperature matrix for the heated bay is x0={T1,T2,T3,T3,T4,T5}x_0 = \{T1, T2, T3, T3, T4, T5\}x0 ={T1,T2,T3,T3,T4,T5}. Temperatures for adjacent and sub-adjacent bays were scaled to 0.8 and 0.6 of the heated bay temperatures, respectively.

The temperature input for the ML model is thus x={x0,0.8x0,0.8x0,0.6x0,0.6x0}x = \{x_0, 0.8x_0, 0.8x_0, 0.6x_0, 0.6x_0\}x={x0,0.8x0,0.8x0,0.6x0,0.6x0}. Due to large deformations of the frame after 5 minutes of fire exposure, a time scaling technique (1:12) was applied to extend the smoothed gas temperature-time data, and outputs were scaled back at a ratio of 12:1.

4.2.3. Results and Analysis

Fire Center Identification: Fig. 20 shows the identification results for the fire center at various exposure times. The model achieved satisfactory approximations, though identification errors increased slightly with fire exposure due to frame deformation.

Temperature Prediction: Fig. 21 presents the predicted maximum gas temperatures at different fire exposure times. The model effectively predicted temperature development based on the identified fire state. However, discrepancies between predicted and actual temperatures arose due to:

- The scaled nature of the test frame affecting geometry dimensions and predictions.
- Structural damage, such as roof destruction, which altered ventilation and fire dynamics.
- Inaccuracies in thermocouple positioning compared to the model's design.

The trained agent provided real-time identification and predictions (2.15 seconds per prediction), suitable for practical use given the time prediction interval (20 minutes after scaling).

4.2.4. Comparison of ML Models

Fire test data were used to evaluate ML models with different weight hyperparameters α\alphaα and network layers (LSTM vs. TCN).

4.2.5. Results Summary (Table 9)

Identification accuracy for fire state increased with higher α\alphaα, though prediction accuracy decreased sharply.

LSTM networks slightly outperformed TCN networks in fire location identification, while both demonstrated satisfactory performance in temperature prediction.

4.3. Full-Scale Fire Test

4.3.1. Test Setup

A fire test was conducted on a full-scale, abandoned building that used to be a factory (Li et al., 2024), as shown in Fig. 22(a). The building dimensions were approximately 11.6 m span, 7 bays with 2 m column spacings, and an average height of 5 m. The geometry matrix for the ML model was g={11.6,6,5,7}g = \{11.6, 6, 5, 7\}g={11.6,6,5,7}, with the column spacing scaled to 6 m, the lower boundary for the model training.

Gas temperatures around the middle 5 bays were measured using thermocouples (Fig. 22(b)).

4.3.2. Test Observations and Data Handling

The fire test lasted about 60 minutes before significant structural deformations occurred. Seven thermocouples, indicated in red in Fig. 22, were found to be damaged based on abnormal data after lateral analysis.

The correlation coefficient and standard deviation-based solution from Section 4.1 were used to successfully locate and repair the damaged thermocouples.

The repaired temperature matrix, along with the geometry matrix, was fed into the trained ML model for temperature predictions.

4.3.3. Results and Analysis

- **Fire Location and Heat Release Rate:** Identifying the exact fire center was challenging due to the complex combustion reactions and varying ignition times of the wood piles. The identified fire location was marked on the wood pile stacking floor plan (Fig. 23(a)). The identified heat release rate, compared with the real rate derived from measured mass loss of the wood piles, showed slight deviations but was sufficient to assist firefighters (Fig. 23(b)).
- **Temperature Predictions:** Fig. 24 shows temperature predictions for typical thermocouples at 20 min, 30 min, and 40 min fire exposure times. Predictions were generally satisfactory, though there were discrepancies at 20 min for thermocouple G3, likely due to early-stage temperature variations. The trained agent provided real-time predictions, taking 1.83 seconds per prediction with a 20-minute interval.
- **Impact of Damaged Thermocouples:** When temperatures from damaged thermocouples were used without repair, the identified fire parameters were significantly affected—fire locations could be misplaced, and heat release rates could even be negative. The temperature predictions were less affected by these damaged thermocouples (Fig. 25). The challenge stems from the fact that damaged thermocouples produce abnormal temperature fields, complicating the model’s ability to correctly identify fire parameters.

4.3.4. Comparison of ML Models:

The fire test data were also evaluated using ML models with different weight hyperparameters α\alphaα and network layers as detailed in Section 5.2. Table 10 shows the prediction accuracy for gas temperatures of the most affected bay with a 20-minute time prediction interval.

Accuracy Trends: Prediction accuracy decreased as α\alphaα increased. The LSTM network performed better than the TCN network in terms of prediction accuracy for this full-scale test.

5. Conclusions

- **ML Framework Efficiency:** The study introduces an ML framework using Long Short-Term Memory (LSTM) and Fully Connected (FC) layers for real-time identification of fire parameters and temperature forecasting in large-span building fires. The model is initially trained on a basic dataset from classical fire models and then refined using an accurate dataset from FDS simulations, demonstrating effectiveness and robustness in fire parameter identification and temperature prediction.
- **Transfer Learning:** Transfer learning from a basic fire dataset to a more refined field model has been proven effective, as evidenced by the real fire test data. This approach enhances the model's accuracy and efficiency.
- **Adaptability and Accuracy:** The ML model adapts well to uncertain factors in real fires, such as changes in ventilation and combustibles burnout. It achieves high identification accuracy for fire locations (over 92%) and temperature predictions (over 89%) with a 20-minute lead time, based on real fire tests.
- **Applicability to Large Spaces:** The trained agent shows good performance on previously unknown datasets for large-space buildings with varying fire scenarios and dimensions, making it suitable for steel portal frames of different sizes under complex fire situations.
- **Handling Damaged Thermocouples:** The model can identify and repair damaged thermocouples using correlation coefficients and standard deviations, with minimal impact on temperature prediction accuracy.

Limitations

- **Sample Variability:** While the model performs well on most test data samples, there can be large errors for some samples. Future work will include incorporating physical constraints related to fire evolution laws to improve model accuracy and safety.
- **Ventilation Effects:** The model's robustness in identifying fire intensity is affected by changes in ventilation conditions. Further improvements are needed to handle these variations more effectively.
- **Thermocouple Damage Limits:** The model may struggle to detect and repair thermocouples when the damage ratio exceeds 30%, potentially affecting performance.

5.1. Future Work Directions

- **Incorporate Additional Data:** Future models will include other on-site measurements, such as smoke density and gas flow rate, to enhance robustness in real fires.
- **Fire-Structure Interaction:** Investigate the effects of fire-structure interactions, particularly for structures experiencing large deformations during a fire. This includes integrating bidirectional coupling technologies and adjusting training datasets to reflect structural dynamics accurately.
- **Real-Time Validation:** Conduct more real-time experimental validations and large-space building fire tests to gather sufficient data and improve practical application.

The study lays a foundation for smart firefighting strategies and identifies areas for further research to enhance model accuracy and applicability in complex fire scenarios.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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