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Real-time Forecast of Compartment Fire and Flashover based on Deep Learning

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Abstract

Forecasting building fire development and critical fire events in real-time is of great significance for firefighting and rescue operations. This work proposes an artificial intelligence (AI) system to fast forecast the compartment fire development and flashover in advance based on a temperature sensor network and a deep-learning algorithm. This fire-forecast system is demonstrated in a 1/5 scale compartment with various ventilation conditions and fuel loads. After training 21 reduced-scale compartment tests, the deep learning model can well identify the fire development inside the compartment and predict the temperature 30 s in advance with relative errors of less than 10%. The flashover can be predicted with a 20-s lead time, and the forecast capacity and accuracy can be further improved with additional test data for training. The AI-forecast model performs well for fires with different fuel types and ventilation conditions and has the potential to be applied to fire scenarios with wider conditions. This research demonstrates the real-time building fire forecast based on Internet of Things (IoT) sensors and AI systems that can help future smart firefighting applications.

Keywords: *Artificial intelligence; Critical fire event; Scaled compartment; IoT; Smart firefighting*

Abbreviations

AI	Artificial intelligence	FPR	False positive Rate
ANN	Artificial neural network	LSTM	Long short-term memory
AUC	Area under the ROC curve	MSE	Mean squared error
CFD	Computational fluid dynamics	RNN	Recurrent neural network
CNN	Convolutional neural network	ROC	Receiver operating characteristic
FDS	Fire dynamics simulator	TPR	True positive Rate

1. Introduction

Enclosed spaces, such as office rooms, classrooms, halls, etc., are the most common building environments in daily life. Statistics show that people spend more than 85% of their time in indoor spaces [1]; therefore, compartment fires occurring in an enclosure room or confined space are the most common fire threat to people [2–4]. Due to the poor ventilation and heat dissipation, compartment fires will grow faster and be more dangerous than fires in open space. In particular, the flashover phenomenon, which is a transition from a localized fire to a global fire, is an essential indicator of compartment fire development [5,6]. Therefore, understanding compartment fire development and the ability to predict flashover have been the long-term hot research topic over the last century.

In compartment fire scenarios, the unburnt fuels will be heated by the radiation from flame and the upper smoke layer, as shown in Fig. 1(a). As the fire grows, the hot smoke will accumulate in the upper part of the compartment, and the radiation effect to the unburnt fuels becomes stronger, accordingly [7]. When the smoke temperature reaches a critical value (i.e., the heat flux is large enough to ignite the unburnt fuels), all the combustible surfaces get ignited almost at the same time [8], marking a steep increase in heat release rate and temperature. This critical phenomenon is defined as flashover [9]. If there is enough fuel, the pyrolysis gas cannot be burnt out inside the compartment, and the fire grows to ventilation controlled after the spontaneous ignition [10]. Then, the spilled flame from the compartment openings can be observed. The above-mentioned criteria continuously happen in a short period, as summarized in Fig. 1(b). Therefore, the flashover is a stage rather than a certain moment.

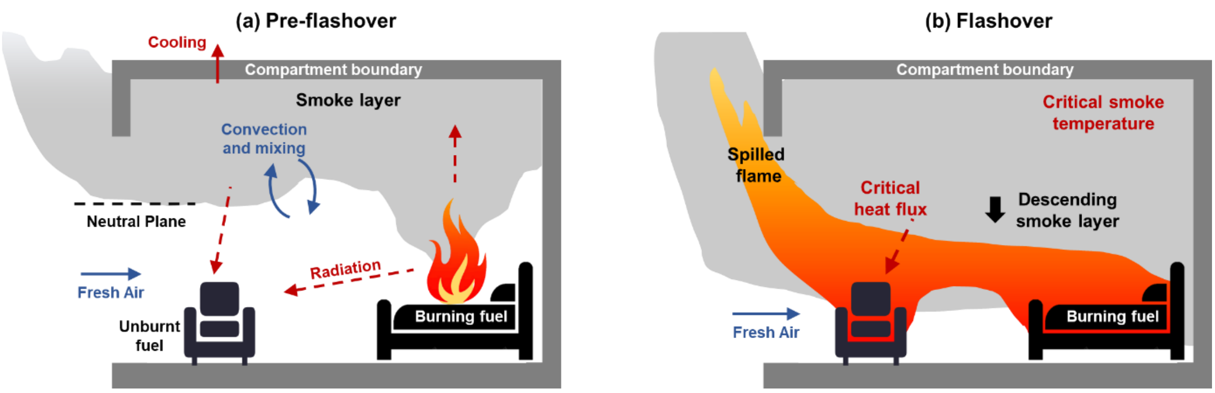

Fig. 1. Diagram of compartment fire (a) pre-flashover stage, and (b) flashover phenomena.

Before the 1950s, the fuel load was considered to be the most important parameter for compartment fire safety [11]. The standard fire temperature test results were widely adopted in the structural fire resistance design [12], although the different stages of compartment fire were still not fully understood. In 1958, Kawagoe's full-scale compartment fire tests concluded that the ventilation factor is the critical parameter to control the fire behaviors and temperature growth inside the compartment [13]. Afterward, the zone model was gradually developed to simulate the pre-flashover stages and was used to predict the limiting conditions of flashover. Based on the zone-model assumption, McCaffrey et al. [14] summarized more than 100 fire test data and proposed the widely adopted MQH correlation for a fixed fire location. These early studies on compartment fire discovered important correlations for the steady-state compartment fire [15], while the understanding of complex spatiotemporal fire evolutions was limited due to the lack of computational tools.

With the fast development of Computational Fluid Dynamics (CFD) methods in the late 1970s and the computational capability in the 2000s, field models were introduced into fire research and building fire engineering design [16]. Several mature CFD software[1], such as FDS/PyroSim, ANSYS Fluent, FireFoam, were then adopted into fire research and largely promoted the understanding of building fire phenomena [17–19]. New concepts, such as the traveling fire and hybrid simulations, were proposed to solve the spatiotemporal fire evolutions [20–24]. However, the CFD fire modeling is time-consuming in both setting up the model and computing the results. For example, prior knowledge about the building, fire location, fuel distribution, and smoke ventilation conditions is required to build a CFD model . Also, the performance of the model is sensitive to the meshing and initial conditions, as well as the user's knowledge and experience [25]. In the 2010s, the data-driven method was introduced to predict compartment fire growth [26–29]. Different optimization methods [28–32] were adopted, whereas the computational speed was improved with the simplification of the model and the sacrifice of forecast accuracy and capacity.

In recent years, artificial intelligence (AI) methods, particularly deep learning models, have become widely used in data analysis, such as machine translation and imaging recognition [33]. These AI methods are also gradually adopted in fire research and smart firefighting [34–36]. For example, Lee and co-workers [19,37] developed a hybrid artificial neural network (ANN) model to predict the temperature distribution in a compartment fire, and was verified by CFD simulations. Kim and Lattimer [38] established a classification model to identify fire and smoke in real-time to support autonomous navigation for smart firefighting robots. Dexters et al. [39] adopted a machine learning method to determine the occurrence of flashover under given fire scenarios. Wang et al. [40] proposed a data recovery algorithm, 'P-flash' that can recover the missing data in case of a sensor was destroyed in a multi-compartment fire. Based on a large numerical database and the deep learning method, Wu et al. [41,42] successfully forecast the tunnel fire development and smoke spread 60 s in advance. Su et al. [43] developed an innovative AI tool to assist the fire engineering performance-based design in the atrium. Wang et al. [44,45] proposed smoke and fire image-based deep-learning method to identify the fire heat release rate in real time.

However, most previous AI fire-prediction models were developed based on fire simulation data, instead of experimental data and real-time sensor data measured from fire scenes. Some focused on predicting the steady-state fire conditions (e.g., the fire location and size and the flashover criteria), but

[1] Certain commercial entities, equipment, or materials may be identified in this document in order to describe an experimental procedure or concept adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the entities, materials, or equipment are necessarily the best available for the purpose.

few could predict the real-time fire development and forecast critical fire events (e.g., flashover and backdraft) in advance. Therefore, more robust AI models with Internet-of-Things (IoT) sensor networks are needed to forecast critical fire events in advance and support on-site firefighting.

This study develops a deep learning AI fire-forecast system that can predict temperature growth and the occurrence of flashover in advance, based on a temperature sensor network and a deep-learning algorithm. The fire-test database includes a set of reduced-scale compartment fire tests with various ventilation conditions and fuel loads. The training database by the deep learning model adopts the temporal temperature data and fire state (flashover or not). Finally, this AI fire-forecast system is validated and demonstrated by experiments, supporting future smart firefighting applications.

2. Methodology

2.1. Scaled compartment model fire test

Building a big database is the foundation of training and applying a deep learning model. Herein, a series of small-scale experiments were conducted with different fuel loads and ventilation conditions. The main structure of the model compartment was made of 4 mm thick galvanized steel, and one of the side walls was made of refractory glass to observe the fire behavior and smoke movement, as shown in Fig. 2. The compartment was a cubical structure with a side length of 0.5 m, roughly a 1/5 scale model. The compartment exterior was covered by 5-cm thick asbestos boards to reduce the cooling. The front panel was designed to be detachable for modification of different ventilation conditions.

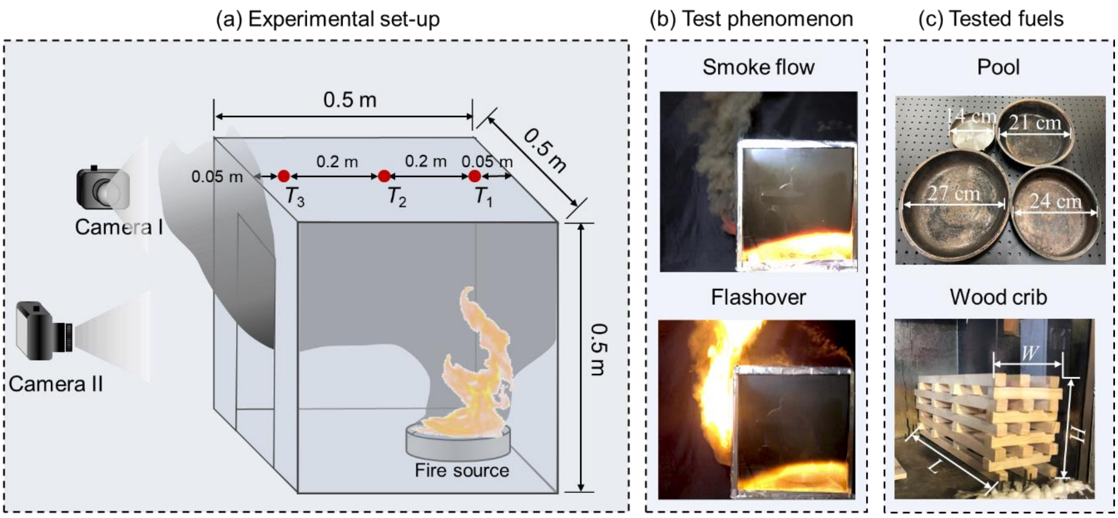

Fig. 2. (a) Diagram of the experimental system, (b) smoke movement and flashover, and (c) tested fuels.

Propanol, ethanol, and wood crib were used as the fuel in the experiments. The parameters of the fuel are demonstrated in Fig. 2(c), where for the liquid fuel, circular pools with diameters ranging from 14 cm to 27 cm were used. The initial thickness of fuel was 3 cm. Wood crib with two different sizes were adopted, i.e., the large one of 40 cm(l)×15 cm(w)×27 cm(h), and the small one of 30 cm(l)×15 cm(w)×21 cm(h). 20 mL propanol was used to quickly ignite the wood crib. The test cases are summarized in Table 1. The fire tests were repeated twice to reduce the random uncertainty.

Table 1. Summary of all test conditions, where Test Nos. 1-21 are used for training the AI model, and Nos. 22-23 are used for testing.

Test No.	Fuel type	Fuel size or diameter (cm)	Opening size *h* (cm) × *w* (cm)
1-3	Propanol	21, 24, 27	40 × 16
4-6	Propanol	21, 24, 27	25 × 25
7-9	Propanol	21, 24, 27	16 × 40
10, 11	Wood crib	Large, small	40 × 16
12, 13	Wood crib	Large, small	25 × 25
14, 15	Wood crib	Large, small	16 × 40
16, 17	Wood crib	Large, small	30 × 30
18, 19	Wood crib	Large, small	30 × 20
20, 21	Wood crib	Large, small	15 × 15
22	Ethanol	24	40 × 16
23	Propanol	14	40 × 16
24	Wood crib	Large	20 × 30

2.2. Compartment fire processes

Two kinds of fire cases (i.e., the liquid pool fires and the wood crib fires) associated with the typical temperature growths are presented in Fig. 3. The fire development processes are shown in Fig. 4. Three stages (growth/pre-flashover, fully-developed/post-flashover, and decay) can be observed. For the liquid pool fire, 40 s after ignition, the temperature increased rapidly to 600 °C. Then, the flame kept growing due to the heat feedback from the hot smoke and compartment to the pool at a relatively small rate. Around 320 s, the small flame spilled through the opening intermittently, indicating the fuel-controlled fire was transitioning to the ventilation-controlled fire, marking the onset of flashover. At 410 s, the fire was completely controlled by ventilation, and continuous spilled flame was observed. The temperature tended to be quasi-stable, so the compartment fire reached the fully developed stage.

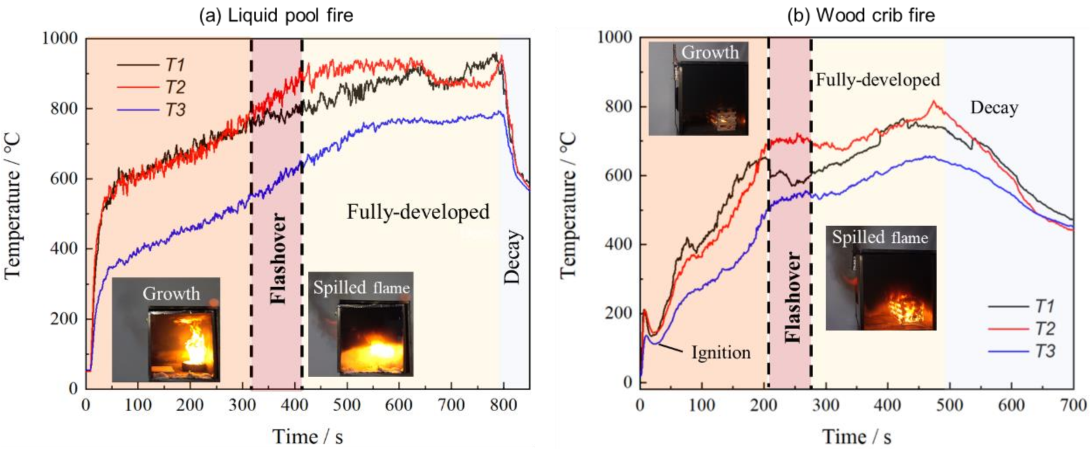

Fig. 3. Typical temperature growth for different fuels (a) 24-cm diameter liquid pool fire with 0.4 m(*h*) × 0.16 m(*w*) opening, and (b) Large wood crib fire with 0.2 m(*h*) × 0.3 m(*w*) opening.

For the wood crib fire, the same three stages can be observed as shown in Fig. 3b. *T1* increases to 600 ℃ at around 180 s, which is much slower than the liquid pool fire. However, unlike the pool fire case, the wood crib can still spread along the unburnt surface to form a larger fire, as shown in Fig. 4b. Therefore, the ceiling temperature of the wood fire will continue to increase until flashover occurs at around 220 s, after which the fire growth rate is controlled by ventilation. In general, the liquid pool fire grows faster at the initial stage but takes a longer period to reach flashover. Comparativley, the wood crib fire grows slower first and then reaches flashover quickly.

Strictly speaking, the real "flashover" was not a short moment but a process involving several critical fire events, such as the spilled flame, the descending smoke layer, and the ignition of all fuels [6]. Herein, the flashover was defined by observing the spilled flame occurrence from the perspective of ventilation. For example, the flashover stage from 320 s when the intermittent spilled flame first observed, to 410 s when the spilled flame became continuous in Figs. 3(a) and 4(a).

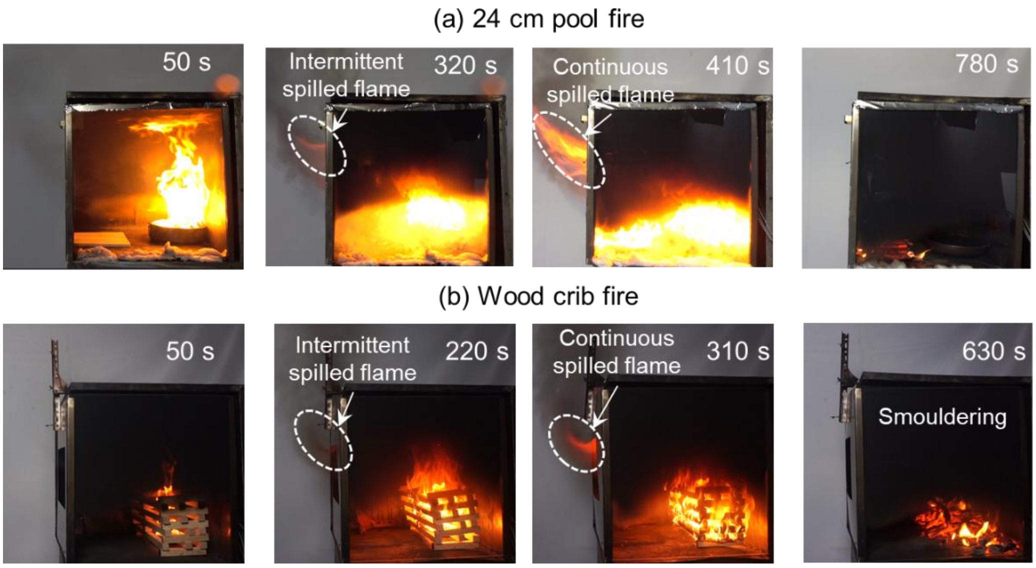

Fig. 4. The fire development process for (a) 24 cm pool fire, and (b) wood crib fire.

2.3. Database generation

An experimental database with various ventilation factors and fuel loads was generated to support the training of the deep learning model. The framework of the database is shown in Fig. 5. The sample space consists of three dimensions: 1) Fuel load, which contains the pool fires with different pan diameters, and the wood fires with different sizes; 2) Opening size, which represents the different ventilation conditions; and 3) Time sequence, which represents the lasting time of the compartment fire. For each compartment fire test case, the temperature data measured by three thermocouples were scanned by a rolling window and stored as the input information to the deep learning model. By conducting a set of initial time length independence studies (Fig. A1), the length of the rolling window was set as 20 s, i.e., three temperature data per second to form a 3×20 data matrix. Thus, the input data for the *n*th rolling window can be written as

$$X_n = \begin{bmatrix} T_{1,n}, T_{1,n+1}, T_{1,n+2} \cdots T_{1,n+20} \\ T_{2,n}, T_{2,n+1}, T_{2,n+2} \cdots T_{2,n+20} \\ T_{3,n}, T_{3,n+1}, T_{3,n+2} \cdots T_{3,n+20} \end{bmatrix} \tag{1}$$

where T represents the temperature data, the first subscript represents the thermocouple number, and the second subscript represents the sampling time.

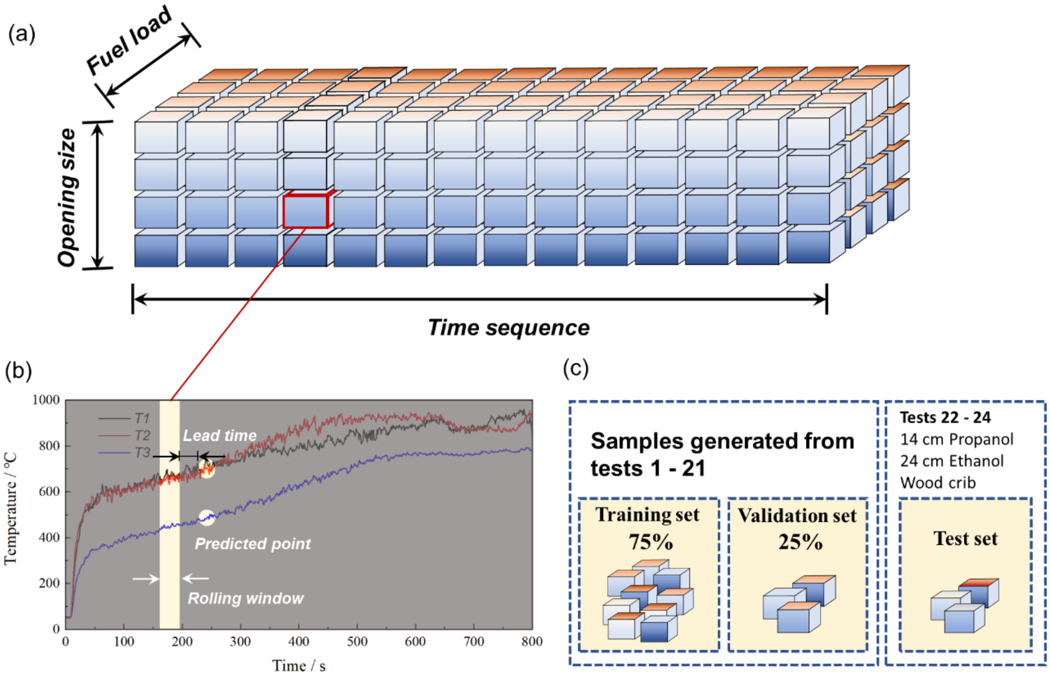

Fig. 5. The framework of the experimental database: (a) structure of the sample space, (b) generation process of sample, taking test 2 as an example, and (c) partitioning of the database

To train the deep learning model, all the input data should be labeled with an expected output in the database [41]. In this paper, the output is the future temperature and the compartment fire state (flashover or not) with a certain period in advance. A relatively short period of 10 s was set as the prediction lead time initially to test the prediction capabilities of the deep learning model. Longer leading times will be tested and discussed subsequently to investigate the maximum temporal predicted ability of the deep learning model. For forecasting temperature data, the temperatures after 10 s of three thermocouples were selected as output.

For forecasting flashover, the fire state is labeled as the flashover probability. It is valued as 0 if no spilled flame was observed after 10 s, and it is valued as 1 if stable and continuous spilled flame can be seen. For the intermittent spilled flame stage, the flashover probability was calculated by the ratio of time with spilled flame in a certain period. For example, if the spilled flame lasted 0.4 s in 1 s, then the flashover probability is regarded as 0.4. Hence, the output for the n^{th} time window was written as

$$Y_n = \begin{Bmatrix} [T_{1,n+30}, T_{2,n+30}, T_{3,n+30}] \\ [\text{flashover probability}] \end{Bmatrix} \tag{2}$$

Based on the method mentioned above, the temporal temperature data obtained from the model tests with various ventilation conditions and fuel loads can be divided as the sample matrix, as shown in Fig. 5(a) and (b). Each of the samples contains temperature sequence data and future fire information (temperature and the occurrence of critical events). According to equation (2), $t - 30$ fragments can be generated for a case lasting t s. In total, 11, 958 samples were generated in the sample matrix and then be divided into training, validation, and test set, as shown in Fig. 5(c).

Specifically, Test Nos. 1-21, i.e., samples of liquid fuel with 21 cm to 27 cm pool diameter and wood crib fires with different opening sizes, were adopted as the training set and validation set with the ratios of 75% and 25%, respectively. To better test the generalization ability of the proposed model, the test set was built by cases that were different from the training and validation set. Therefore, samples generated from Test Nos. 22-24, i.e., 14 cm propanol pool fires, 24 cm ethanol pool fire, and the wood crib fire, with an opening size different from the training set were selected as the test set.

2.4. The framework of the Deep Learning algorithm

In this work, we aimed at predicting the fire development and critical event (flashover) on the basis of the historical temperature information with time series. Therefore, the Long Short-Term Memory (LSTM) neural network, which was designed for the regression and classification of temporal data, was introduced to facilitate the prediction of the model compartment fire development. The LSTM network was built with TensorFlow Core v2.2.0 [46]. The basic LSTM unit and the model structure are demonstrated in Fig. 6. Compared with traditional Recurrent Neural Network (RNN), LSTM could mitigate the potential gradient disappearance (or explosion) by introducing the concept of the gate, as shown in Fig. 6(a). Therefore, LSTM was particularly suitable to extract key information from long sequential temporal data [47,48].

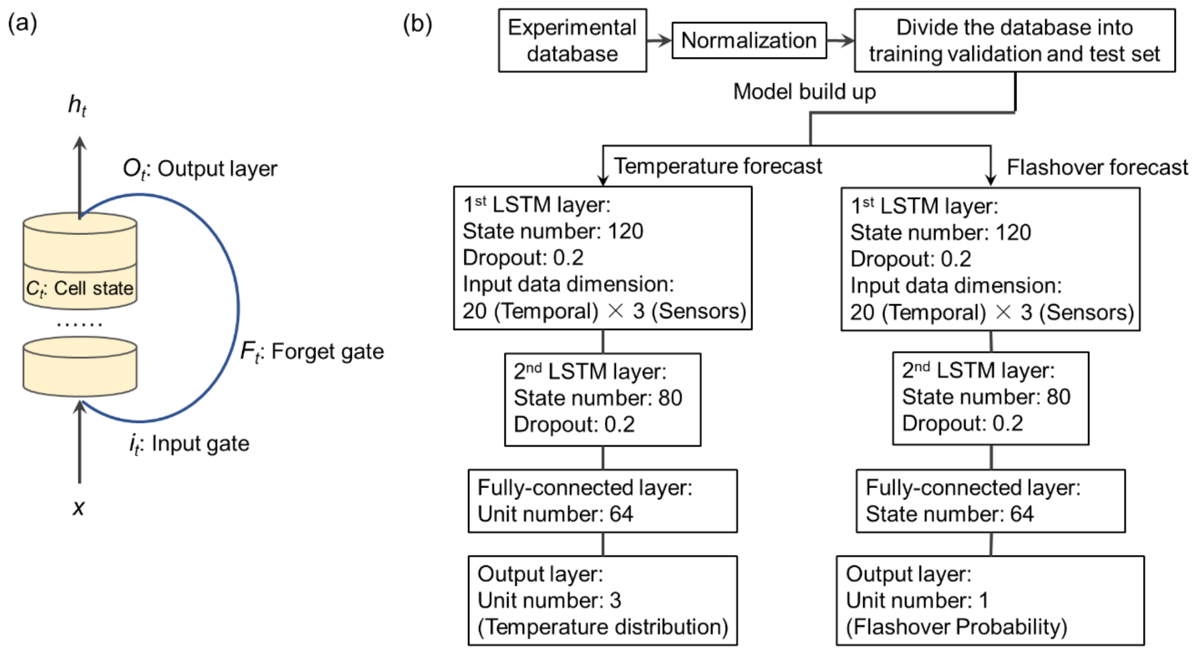

Fig. 6. (a) The basic unit of the LSTM network, (b) the structure of the compartment fire forecast model.

Fig. 6(b) shows the structure of the compartment fire forecast model, the samples obtained in section 2.1 were firstly normalized between 0 and 1 using Scikit-learn [49] to avoid the potential influence caused by the data scale [50,51]. The proposed model consists of two sub-models to realize the forecast of temperature and flashover occurrence, respectively. The sub-models share a similar structure except for the output layer. They both consist of two layers with 120 and 80 LSTM units, and a fully-connected layer with 64 units. The output layer for the temperature forecast model has three units to associate with the number of the sensors, and the unit number is one when forecasting flashover to output the flashover probability. An initial dropout rate of 0.2 was set for each LSTM layer to avoid overfitting [52]. 'ReLU' activation function was selected for all hidden layers.

It should be pointed out that although the hyperparameters for the sub-models are almost the same, they are selected and trained individually. This is because in the LSTM layer and Fully-connected layer, the neural network aims to achieve the same target no matter for forecasting temperature and flashover, i.e., extracting the temporal distributed characteristics of the temperature data sequence and non-linearly fitting the output. The current model structure is proven to perform well for the forecast of both the temperature growth and flashover occurrence, as demonstrated subsequently.

The forecast of fire temperature and flashover requires the model to output continuously distributed values, i.e., temperature values and the flashover probability (reflected by the continuity of spilled flame), which can be treated as regression problems. Therefore, mean squared error (MSE) and coefficient of determination (R^2) was adopted as the loss function and metrics for their good performance on the regression problems [53]. The initial learning rate and training epochs were set as 0.0003 and 200 according to preliminary trials. The temporal features of the compartment fire temperature development were extracted by the LSTM network at each time step. The correlation was stored into the parameters of each neural unit of the network and can be applied to predict the temperature evolution and critical fire event for unknown compartment fires.

3. Results and discussions

3.1. The training process for temperature and flashover

The AI model performance and the accuracy of the training set and validation set during the training process are shown in Fig. 7. Different performances are observed when training although the two sub-models share similar model structures. For predicting the compartment temperature in Fig. 7(a), the value of R^2 (i.e., coefficient of determination) increased to more than 0.85 within 10 epochs, and the loss curve quickly decreased to lower than 0.01. For predicting flashover in Fig. 7(b), the growth rate of accuracy and the decrease rate of loss with training epochs were much slower. As expected, because the flashover phenomenon is a transition state in the compartment fire, its occurrence is sensitive to many random factors and of high uncertainty [54], as reflected by many local peaks in both curves of Fig. 7(b). Another reason is that using the temperature to predict flashover requires the deep learning model to build a more complex correlation between the two different parameters compared with using historitical temperature to predict temperature, which adopts a parameter to predict the same parameter. Therefore, a longer training process was needed to extract features of flashover occurrence in a complicated fire system.

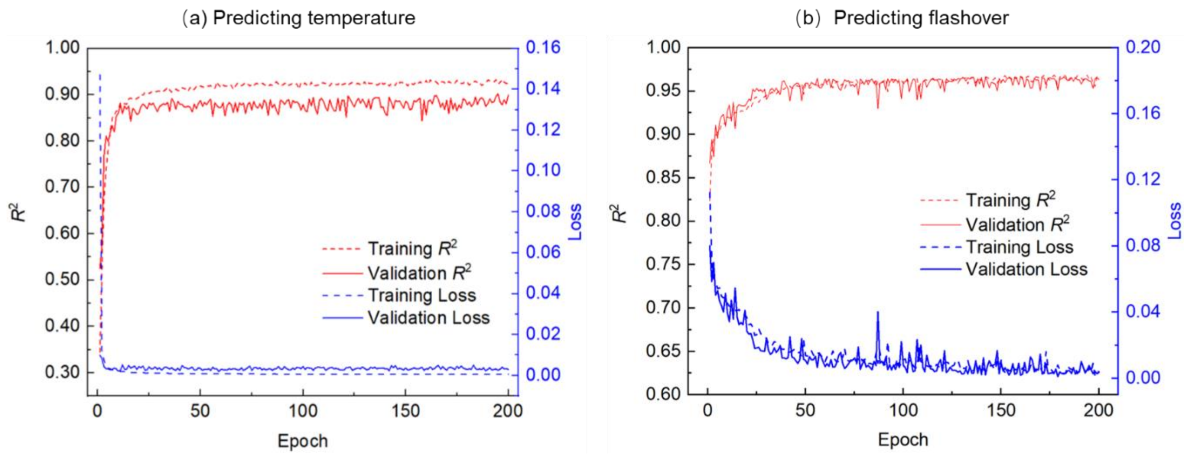

Fig. 7. The loss and accuracy curve when training the sub-models (a) temperature, (b) flashover.

3.2. Deep learning model test

The real-time predictions of temperature and flashover 10 s in advance are demonstrated by reduced-scale experiments in Videos S1 (14 cm pool fire), S2 (24 cm pool fire), and S3 (wood crib fire), where the openings are 0.4 m(h) × 0.16 m(w), 0.4 m(h) × 0.16 m(w), 0.2 m(h) × 0.3 m(w), respectively. The prediction starts at 20 s, as the model requires inputting 20-s temperature data. Note that in the videos, the prediction (red dash line) is 10 s ahead of the reality (black solid line), and the flashover probability is defined by the intermittent rate. The forecasted temperature and flashover are accurate, demonstrating a good fire forecast capability of the proposed deep-learning model.

More quantitative analyses for the predicted temperature and flashover probability with 10 s leading time are shown in Fig. 8. For the 14 cm diameter pool fire, the temperature growth can be well predicted by the LSTM model with a maximum error of less than 100 ℃, although the fuel load is far smaller than the minimum fuel load in the training set (21 cm pool fire), as shown in Fig. 8(a). It is also observed that the relative prediction error distributes between -20% to 20%, and more than 40% of prediction error points are concentrated in the ±10% region, according to Fig. A2(a). For the flashover prediction, since the fire load is insufficient to induce flashover, the fire state keeps a constant 0, as presented by the red line in Fig. 8(b). The predicted value of the proposed LSTM model is also small (no more than 0.15), indicating a very low probability for flashover occurrence, which matches the reality well.

For the 24 cm diameter pool fire, the predictions also agree well with the real temperature data, with a relative error of less than 10%, shown in Figs. 8(b) and A2(b). For predicting flashover, the forecasted value keeps 0 at the beginning 165 s, and then gradually approaches 1 at 228 s. In the experiment, spilled flame occurs at 168 s and becomes continuous at around 230s. Between this stage, the intermittent spilled flame rate fluctuates from 0.3 to 0.5 for about 40 s, whereas the predicted value keeps increasing. Although a difference exists between the observation and the prediction, the start point of the spilled flame occurrence and the transition point from intermittent to continuous spilled flame are both well predicted by the deep learning model, as shown in Fig. 8(b) and Video S2.

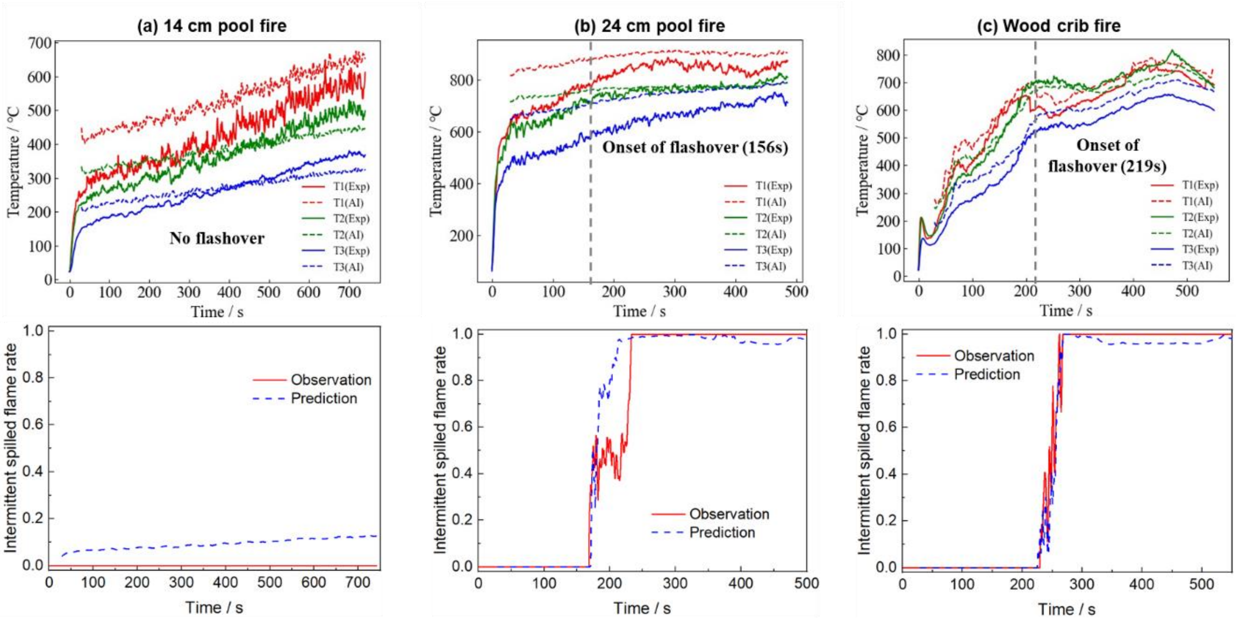

Fig. 8. Prediction of temperature and flashover probability by the Deep Learning model for (a) 14 cm liquid pool fire, (b) 24 cm liquid pool fire, and (c) wood crib fire, where the solid lines are the experimental measurements, and the dashed lines are predictions.

For the wood crib fire case, in the first 10 s ignition period, the burning of liquid pool fire provides the major contribution for the rapid temperature rise. Afterward, the burning of wood dominants and the temperature rises in a much slower way after the liquid fuel is burnt out. The predicted temperature fits well with the reality, as shown in Fig. 8(c), and the relative error distributes between -10% to 10%, as shown in Fig. A2. For the flashover prediction of the wood fire, spilled flame occurs at 219 s and becomes stable at 269 s in reality. Unlike the liquid pool fire, the wood fire experiences a shorter transition stage without fluctuations, and the increasing trend can be accurately predicted by the deep learning model, as shown in Fig. 8(c) and Video S3.

In conclusion, the proposed model can fit fire scenarios with different development characteristics, e.g., no-flashover case, fast-developed liquid pool fire case, and slow-developed wood crib fire case. Basically, the variation of the fuel type and ventilation conditions affect the fire growth rate of the compartment fire. These differences are reflected by the evolution of temperature profile and flashover probability. Since the proposed deep learning model performs well on forecasting the growth of temperature and intermittent spilled flame rate for cases with fuel diameter, fuel type, and opening size out of the training set, it is believed that the model has the potential to be applied to wider fire scenarios.

3.3. The forecast capability of the deep learning model

In the above section, it has been proved that the proposed LSTM network can well predict temperature development and flashover occurrence for pool fire 10 seconds in advance. To test the forecast capability of the deep learning model, the predicted temperature and flashover for the 24 cm pool fire with different lead times (10 s, 20 s, and 30 s) are presented together in Fig. 9. For these figures, only output in Fig. 5 is replaced by the temperature data and fire state with different lead times when generating the database, and all other parameters and processes are kept the same.

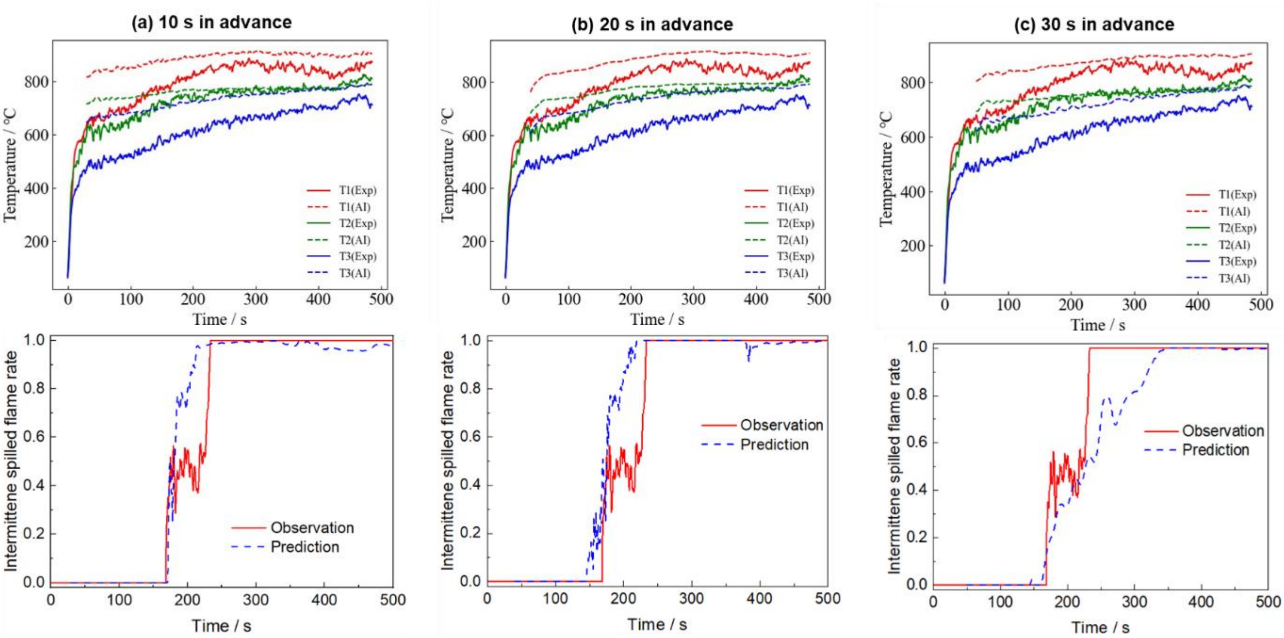

Fig. 9. Prediction of temperature and flashover probability by the deep learning model (a) 10 s in advance, (b) 30 s in advance, and (c) 60 s in advance, where the solid lines are the experimental measurements, and the dashed lines are predictions.

According to Fig. 9, no obvious difference can be observed for the predicted temperature (see the error distribution in Fig. A3. Most of the predicted temperature error lies on the ±10% region even the predicted period increases to 30 seconds. The results indicate that the temperature prediction is insensitive to the predicted period. Another possible reason may be that the temperature basically does not change much during these time intervals.

For the flashover forecast, the predicted value agrees well with the real flashover time with a 10 s lead time. However, the model predicted a 20 s earlier time for the occurrence of flashover, and a near accurate time for the continuous spilled flame, as shown in Fig. 9(b). The results became even worse when the lead time was set as 30 s. The model outputs a heavy delay (more than 100 s) for the fully-developed fire, as shown in Fig. 9(c). This is extremely dangerous for real firefighting since it already reaches the tenable conditions for people to survive but the safe conclusion is predicted by the model.

Once a certain threshold of intermittent spilled flame rate is given to identify the fire states, i.e., flashover and no flashover, then the flashover forecast performance of the deep learning model can be evaluated as a classification model. Herein, the ROC (Receiver Operating Characteristic) curves and corresponding AUC (Area under the ROC curve) with different lead times are demonstrated in Fig. 10

to quantitatively evaluate the model performance. As shown, the deep learning model can predict flashover 10s in advance with an AUC value of 0.93, indicating a nearly perfect prediction. AUC value decreases to 0.87 when the lead time increases to 20 s, which is still acceptable. However, the AUC value decreases to 0.79 when the lead time increases to 30 seconds, which is only a little better than a random prediction (AUC=0.5).

In general, temperature growth can be predicted with a longer lead time than flashover. One major reason is that the flashover phenomenon itself has a large uncertainty and is sensitive to the many influential factors. The long-term prediction is always more challenging and less accurate for a complex and chaotic system, similar to the weather forecast. It should also be noted that the available data will become fewer as the lead time becomes longer.

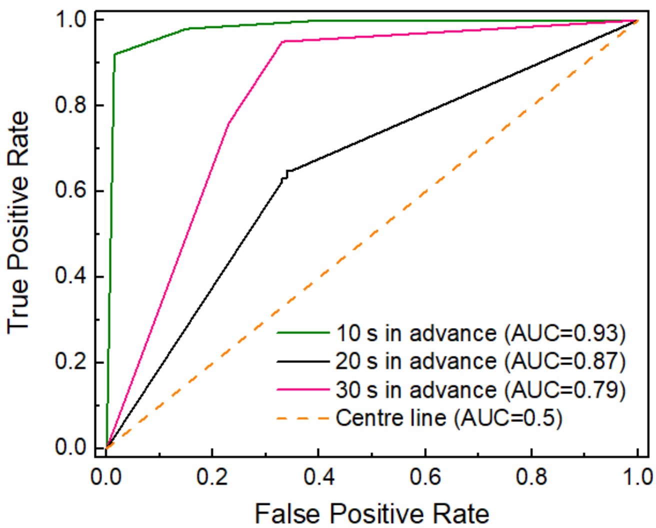

Fig. 10. The ROC curve for different prediction lead times.

The other reason for a more accurate forecast of temperature is that the input training data is also temporal temperature data. Therefore, using the previous temperature to predict future temperature is similar to a conventional problem of Newton polynomial interpolation. In other words, the deep learning model proposed an unknown non-linear fitting correlation by analyzing the data distribution and derivatives in the training process. On the other hand, forecasting the flashover (i.e., output) with the temperature data (i.e., input) requires the deep-learning model to establish a more complex correlation between these two different parameters. Such a correlation should touch the physics of fire processes and correlate multi-dimensional information, which is too complex to be expressed analytically. Therefore, the AI method mimics the intuition of experienced firefighters in forecasting critical fire events by matching patterns from past fire scenarios (i.e., database in the brain).

Finally, it should be noted that the fire scenarios designed in the experiments were simplified under the lab environment so that the fire and temperature develop at a relatively smooth level, and neither large temperature fluctuations nor data discontinuity was observed. However, in real fire scenarios or large-scale fire tests, the sensor data may be more unstable with larger noises, and sensors can provide incomplete or false data when they are destroyed by high-temperature fire and smoke. All of these issues will increase the difficulties for the fire prediction. Thus, long-term developments of reliable IoT sensor networks and more accurate AI models are expected to forecast real building fires and support smart firefighting.

4. Conclusions

This work proposed a framework to forecast both the compartment fire development and the occurrence of flashover with lead time using IoT temperature sensors and a deep learning AI model. This concept was demonstrated in a 1/5 scale compartment with test data of various ventilation factors and fuel loads. After training 21 reduced-scale compartment tests, the deep-learning model could well forecast the temperature inside the compartment with a lead time of 30 s, where the relative error is no more than 10%. Compared to forecasting temperature, forecasting the occurrence of flashover in advance is more challenging, and the current model can predict an acceptable result for the occurrence of flashover with a lead time of 20 s. The model performs well for fires with different fuel types (liquid fuel and wood cribs) and ventilation conditions. Thus, once trained by more test data of different fire scenarios and scales, the AI model has a great potential to forecast fire scenarios and critical fire events in real firefighting operations and emergency response.

The future database will include more fuel types and load conditions and compartment size and ventilation conditions to enhance AI's forecast capability. Moreover, additional data from different sensors and fire images and videos, such as heat flux, flame behaviors, smoke visibility, flow pattern, and color, will be collected with the development of IoT sensor networks and smart buildings. These data will be trained together with many fire scenarios (both experimental and numerical data) in the AI model to provide a better forecast of building fire development and critical events.

CRediT authorship contribution statement

Tianhang Zhang: Investigation, Methodology, Writing - original draft, Formal analysis. **Zilong Wang:** Investigation, Writing - review & editing. **Ho Yin Wong:** Investigation, Resources. **Wai Cheong Tam:** Formal analysis, Writing - review & editing. **Xinyan Huang:** Conceptualization, Supervision, Writing - review & editing, Funding acquisition. **Fu Xiao:** Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] L. Wallace, Indoor Particles: A Review, Journal of the Air and Waste Management Association. 46 (1996) 98–126. https://doi.org/10.1080/10473289.1996.10467451.

[2] P. Brushlinsky, N.N. Ahrens, M. Sokolov, S.V. and Wagner, “World fire statistics”, CTIF, International Association of Fire and Rescue Services, No. 22, (2016).

[3] D. Cortés, D. Gil, J. Azorín, F. Vandecasteele, S. Verstockt, A review of modelling and simulation methods for flashover prediction in confined space fires, Applied Sciences (Switzerland). 10 (2020) 1–18. https://doi.org/10.3390/app10165609.

[4] V. Babrauskas, R.D. Peacock, P.A. Reneke, Defining flashover for fire hazard calculations: Part II, Fire Safety Journal. 38 (2003) 613–622. https://doi.org/10.1016/S0379-7112(03)00027-4.

[5] D.J. Rasbash, Major fire disasters involving flashover, Fire Safety Journal. 17 (1991) 85–93.

[6] B. Karlsson, J. Quintiere, Enclosure Fire Dynamics, 1999. https://doi.org/10.1201/9781420050219.

[7] V. Babrauskas, FIRE ENDURANCE IN BUILDINGS., University of California, Berkeley, 1976.

[8] P.H. Thomas, Testing products and materials for their contribution to flashover in rooms, Fire and Materials. 5 (1981) 103–111.

[9] R.D. Peacock, P.A. Reneke, R.W. Bukowski, V. Babrauskas, Defining flashover for fire hazard calculations, Fire Safety Journal. 32 (1999) 331–345.

[10] D. Drysdale, An Introduction to Fire Dynamics, 3rd ed., John Wiley & Sons, Ltd, Chichester, UK, 2011. https://doi.org/10.1002/9781119975465.

[11] P. Thomas, SFPE classic paper review: Fire behavior in rooms by Kunio Kawagoe, Journal of Fire Protection Engineering. 14 (2004) 5–8. https://doi.org/10.1177/1042391504039408.

[12] S. Magnusson, S. Thelandersson, Temperature-time curves of complete process of fire development, Bulletin of Division of Structural Mechanics & Concrete Construction Bulletin. (1970).

[13] K. Kawagoe, Fire Behavior in Rooms, Report 27, Tokyo, Japan. (1958).

[14] B.J. McCaffrey, J.G. Quintiere, M.F. Harkleroad, Estimating room temperatures and the likelihood of flashover using fire test data correlations, Fire Technology. 17 (1981) 98–119. https://doi.org/10.1007/BF02479583.

[15] M.L. Janssens, Introduction to mathematical fire modeling, CRC Press, 2000.

[16] R., Friedman, An International Survey of Computer Models for Fire and Smoke, Journal of Fire Protection Engineering. 4 (1992) 81–92.

[17] N.D. Pope, C.G. Bailey, Quantitative comparison of FDS and parametric fire curves with post-flashover compartment fire test data, Fire Safety Journal. 41 (2006) 99–110. https://doi.org/10.1016/j.firesaf.2005.11.002.

[18] R. Viall, K. Wiegand, Fire modeling in Fluent, Worcester: Worcester Polytechnic Institute. (2008).

[19] R.K.K. Yuen, E.W.M. Lee, S.M. Lo, G.H. Yeoh, Prediction of temperature and velocity profiles in a single compartment fire by an improved neural network analysis, Fire Safety Journal. 41 (2006) 478–485. https://doi.org/10.1016/j.firesaf.2006.03.003.

[20] G.C. Clifton, Fire models for large firecells, HERA, 1996.

[21] J. Stern-Gottfried, Travelling Fires for Structural Design, Fire Safety Journal. 54 (2011) 74–85. https://doi.org/10.1016/j.firesaf.2012.06.003.

[22] X. Dai, S. Welch, A. Usmani, A critical review of “travelling fire” scenarios for performance-based structural engineering, Fire Safety Journal. 91 (2017) 568–578.

https://doi.org/10.1016/j.firesaf.2017.04.001.

[23] F. Colella, G. Rein, R. Borchiellini, R. Carvel, J.L. Torero, V. Verda, Calculation and design of tunnel ventilation systems using a two-scale modelling approach, Building and Environment. 44 (2009) 2357–2367. https://doi.org/10.1016/j.buildenv.2009.03.020.

[24] B. Ralph, R. Carvel, Coupled hybrid modelling in fire safety engineering; a literature review, Fire Safety Journal. 100 (2018) 157–170. https://doi.org/10.1016/j.firesaf.2018.08.008.

[25] E.N. Lorenz, Deterministic nonperiodic flow, Journal of Atmospheric Sciences. 20 (1963) 130–141.

[26] L. Han, S. Potter, G. Beckett, G. Pringle, S. Welch, S.H. Koo, G. Wickler, A. Usmani, J.L. Torero, A. Tate, FireGrid: An e-infrastructure for next-generation emergency response support, Journal of Parallel and Distributed Computing. 70 (2010) 1128–1141. https://doi.org/10.1016/j.jpdc.2010.06.005.

[27] S. Potter, Critical reasoning: AI for emergency response, Applied Intelligence. 37 (2012) 337–356. https://doi.org/10.1007/s10489-011-0331-y.

[28] W. Jahn, G. Rein, J.L. Torero, Forecasting fire growth using an inverse zone modelling approach, Fire Safety Journal. 46 (2011) 81–88. https://doi.org/10.1016/j.firesaf.2010.10.001.

[29] W. Jahn, G. Rein, J.L. Torero, Forecasting fire dynamics using inverse computational fluid dynamics and tangent linearisation, Advances in Engineering Software. 47 (2012) 114–126. https://doi.org/10.1016/j.advengsoft.2011.12.005.

[30] W. Jahn, Inverse Modelling to Forecast Enclosure Fire Dynamics, (2010).

[31] K.J. Overholt, O.A. Ezekoye, Characterizing Heat Release Rates Using an Inverse Fire Modeling Technique, Fire Technology. 48 (2012) 893–909. https://doi.org/10.1007/s10694-011-0250-9.

[32] M. Price, A. Marshall, A. Trouvé, A Multi-observable Approach to Address the Ill-Posed Nature of Inverse Fire Modeling Problems, Fire Technology. 52 (2016) 1779–1797. https://doi.org/10.1007/s10694-015-0541-7.

[33] M. Tegmark, Life 3.0: Being human in the age of artificial intelligence, Knopf, 2017.

[34] D.P. Bliss, V. President, F. Operations, Creating the Research Roadmap for Smart Fire Fighting, NIST Special Publication 1191. (2015). https://doi.org/10.6028/NIST.SP.1191.

[35] M.Z. Naser, Mechanistically Informed Machine Learning and Artificial Intelligence in Fire Engineering and Sciences, Fire Technology. 57 (2021) 2741–2784. https://doi.org/10.1007/s10694-020-01069-8.

[36] X. Huang, X. Wu, A. Usmani□, Perspectives of Using Artificial Intelligence in Building Fire Safety, in: M.Z. Naser (Ed.), Handbook of Cognitive and Autonomous Systems for Fire Resilient Infrastructures, Springer, 2021.

[37] E.W.M. Lee, R.K.K. Yuen, S.M. Lo, K.C. Lam, G.H. Yeoh, A novel artificial neural network fire model for prediction of thermal interface location in single compartment fire, Fire Safety Journal. 39 (2004) 67–87. https://doi.org/10.1016/S0379-7112(03)00092-4.

[38] J.H. Kim, B.Y. Lattimer, Real-time probabilistic classification of fire and smoke using thermal imagery for intelligent firefighting robot, Fire Safety Journal. 72 (2015) 40–49. https://doi.org/10.1016/j.firesaf.2015.02.007.

[39] A. Dexters, R.R. Leisted, R. Van Coile, S. Welch, G. Jomaas, Testing for knowledge: Application of machine learning techniques for prediction of flashover in a 1/5 scale ISO 13784-1 enclosure, Fire and Materials. 45 (2021) 708–719. https://doi.org/10.1002/fam.2876.

[40] J. Wang, W.C. Tam, Y. Jia, R. Peacock, P. Reneke, E.Y. Fu, T. Cleary, P-Flash – A machine learning-based model for flashover prediction using recovered temperature data, Fire Safety Journal. 122 (2021) 103341. https://doi.org/10.1016/j.firesaf.2021.103341.

[41] X. Wu, Y. Park, A. Li, X. Huang, F. Xiao, A. Usmani, Smart Detection of Fire Source in Tunnel Based on the Numerical Database and Artificial Intelligence, Fire Technology. 57 (2021) 657–682. https://doi.org/10.1007/s10694-020-00985-z.

[42] X. Wu, X. Zhang, X. Huang, F. Xiao, A. Usmani, A real-time forecast of tunnel fire based on numerical database and artificial intelligence, Building Simulation. 15 (2022) 511–524. https://doi.org/10.1007/s12273-021-0775-x.

[43] L. chu Su, X. Wu, X. Zhang, X. Huang, Smart performance-based design for building fire safety: Prediction of smoke motion via AI, Journal of Building Engineering. 43 (2021) 102529. https://doi.org/10.1016/j.jobe.2021.102529.

[44] Z. Wang, T. Zhang, X. Wu, X. Huang, Predicting transient building fire based on external smoke images and deep learning, Journal of Building Engineering. 47 (2022) 103823. https://doi.org/10.1016/j.jobe.2021.103823.

[45] Z. Wang, T. Zhang, X. Huang, Predicting Real-time Fire Heat Release Rate based on Flame Images and Deep Learning, Proceedings of the Combustion Institute (under Review). 39 (2022).

[46] M. Rucci, A. Casile, Fixational instability and natural image statistics: Implications for early visual representations, Network: Computation in Neural Systems. 16 (2005) 121–138. https://doi.org/10.1080/09548980500300507.

[47] Y. Bengio, P. Simard, P. Frasconi, Learning Long-Term Dependencies with Gradient Descent is Difficult, IEEE Transactions on Neural Networks. 5 (1994) 157–166.

[48] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Computation. 9 (1997) 1735–1780.

[49] B. Komer, J. Bergstra, C. Eliasmith, Hyperopt-Sklearn: Automatic Hyperparameter Configuration for Scikit-Learn, Proceedings of the 13th Python in Science Conference. (2014) 32–37. https://doi.org/10.25080/majora-14bd3278-006.

[50] J. Kumar, R. Goomer, A.K. Singh, Long Short Term Memory Recurrent Neural Network (LSTM-RNN) Based Workload Forecasting Model for Cloud Datacenters, Procedia Computer Science. 125 (2018) 676–682. https://doi.org/10.1016/j.procs.2017.12.087.

[51] S. Aksoy, R.M. Haralick, Feature normalization and likelihood-based similarity measures for image retrieval, Pattern Recognition Letters. 22 (2001) 563–582. https://doi.org/10.1016/S0167-8655(00)00112-4.

[52] S. Park, N. Kwak, Analysis on the Dropout Effect in Convolutional Neural Networks, Asian Conference on Computer Vision. (2016).

[53] E.Y. Fu, W.C. Tam, J. Wang, R. Peacock, P. Reneke, G. Ngai, H.V. Leong, T. Cleary, Predicting Flashover Occurrence using Surrogate Temperature Data, (2017).

[54] P.H. Thomas, M.L. Bullen, J.G. Quintiere, B.J. McCaffrey, Flashover and instabilities in fire behavior, Combustion and Flame. 38 (1980) 159–171. https://doi.org/10.1016/0010-2180(80)90048-6.

Appendix

The principal of the LSTM network is to predict future data by learning the temporal characteristics in a data sequence. For the experimental database, on the one hand, if the sequence length is too short, the sample is easily affected by the noise and uncertainty of the tests. On the other hand, near-term data has a higher correlation to determine the future fire state than the far-term data. Therefore, there is an upper limit for improving the prediction accuracy by increasing the data sequence length. As shown in Figure. A1, R^2 increases from 0.92 to 0.96 when the sample length increases from 10 s to 20 s. However, R^2 cannot further grows for longer sample length. Thus, 20 s is selected as sample length, herein.

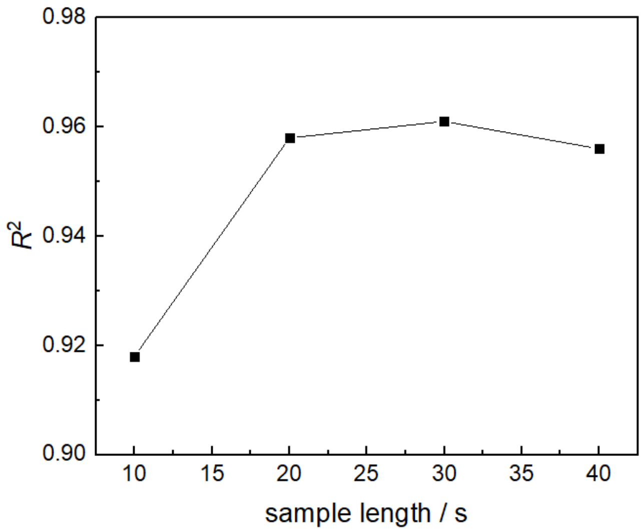

Fig. A1. R^2 of flashover forecast with different sample length after 200 epochs training

Figure. A2 presents the relative error distribution for the temperature prediction of the deep learning model on the different test dataset (i.e., different pool fire sizes and wood crib fires). Figure. A3 presents the relative error distribution for the temperature prediction with three different lead times (10 s, 20 s, and 30 s).

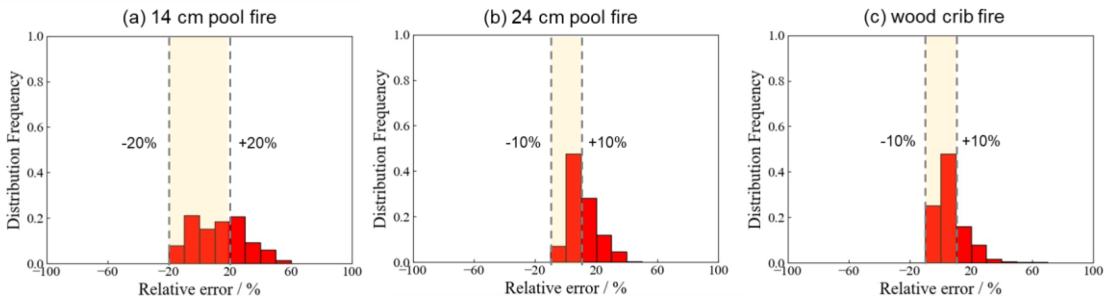

Fig. A2. Relative error distribution for the temperature prediction 10 s in advance for (a) 14 cm pool fire, (b) 24 cm pool fire, and (c) wood crib fire.

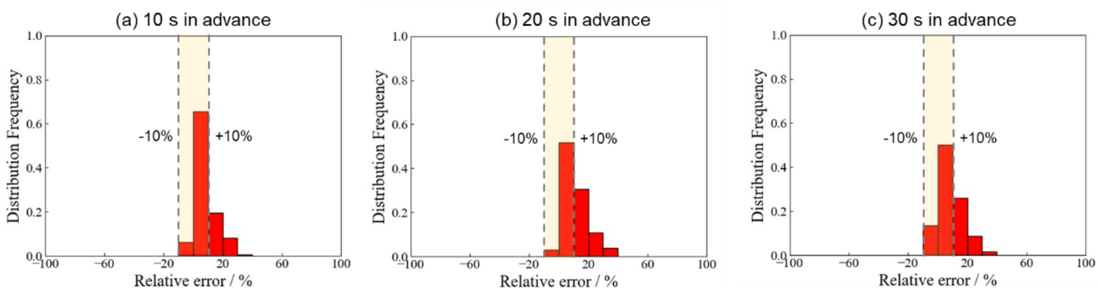

Fig. A3. Relative error distribution for the temperature prediction for 24 cm pool fire (a) 10 s in advance, (b) 20 s in advance, and (c) 30 s in advance.