Predicting Flashover Occurrence using Surrogate Temperature Data

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Abstract

Fire fighter fatalities and injuries in the U.S. remain too high and fire fighting too hazardous. Until now, fire fighters rely only on their experience to avoid life-threatening fire events, such as flashover. In this paper, we describe the development of a flashover prediction model which can be used to warn fire fighters before flashover occurs. Specifically, we consider the use of a fire simulation program to generate a set of synthetic data and an attention-based bidirectional long short-term memory to learn the complex relationships between temperature signals and flashover conditions. We first validate the fire simulation program with temperature measurements obtained from full-scale fire experiments. Then, we generate a set of synthetic temperature data which account for the realistic fire and vent opening conditions in a multi-compartment structure. Results show that our proposed method achieves promising performance for prediction of flashover even when temperature data is completely lost in the room of fire origin. It is believed that the flashover prediction model can facilitate the transformation of fire fighting tactics from traditional experience-based decision marking to data-driven decision marking and reduce fire fighter deaths and injuries.

Introduction

Fire fighters face tremendous dangers on the fire ground. Over the past ten years, nearly 750 fire fighters were killed and approximately 250,000 fire fighters were injured (Campbell et al. 2019; Fahy et al. 2020). Rapid fire progression, such as flashover, has been identified as one of the leading causes for both fire fighter fatalities and injuries. In a fire scenario, flashover is an extreme event. When it occurs, nearly all directly exposed combustible materials, such as a sofa, mattress, and carpeting, in a compartment, such as living room or bedroom, can be simultaneously ignited. Consequently, gas temperature within the compartment increases exponentially, and exceed more than 800 °C (Thomas et al. 1980). Figure 1a shows the compartment gas temperature profile from a flashover fire. In such a high temperature condition, survival for any fully-equipped fire fighter is rare (Dunn 2015).

Although typical indicators of the onset of flashover, such as hot layer gas temperature achieving approximately 550 °C to 600 °C (Peacock et al. 1999) and/or average heat flux at the floor level reaching 20 kW/m^2 to 25 kW/m^2 (Walton et al. 2016), are well known in the fire research community, this kind of detailed information about the interior thermal conditions is not available for nearly all fires. Thus, it is rather difficult for fire fighters to realize the potential fire hazards inside the fire room from outside.

In a structure fire, fire fighters rely on their experience in recognizing the potential occurrence of flashover. According to the most updated fire fighting training manual (Stowell and Murnane 2017), rollover is one possible flashover indicator. Visually, it can be seen as flames spreading across the ceiling outside of the fire room. When rollover phenomenon is observed, a flashover is likely to occur. However, this kind of experience-based indicator is not easy to recognize, and it could take many years of experience to build up the necessary proficiency. Therefore, if fire fighters do not have such a high level of situational awareness, the flashover threat presents itself as an unpredictable life-threatening hazard.

One can save a significant number of lives by developing a data-driven model based on temperature signals from heat sensors within the compartment to warn fire fighters before the flashover occurs. Yet, there are two primary challenges: (1) temperature data in multi-compartment structures are

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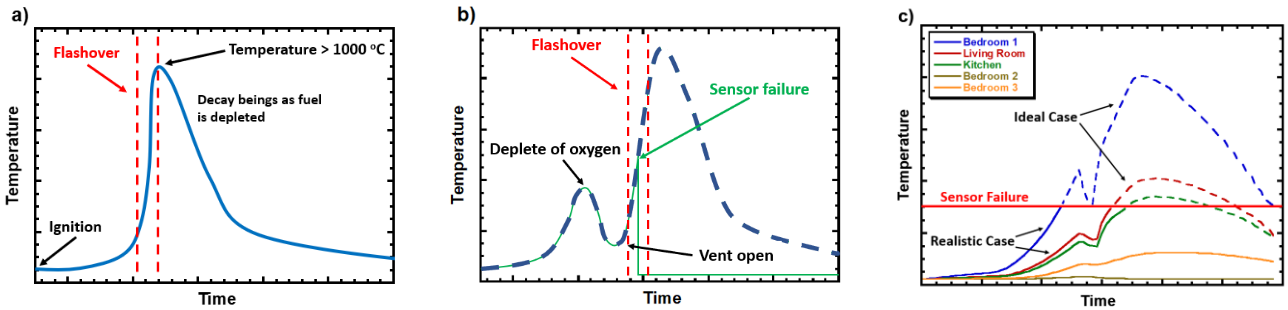

Figure 1: Temperature profile with flashover in a compartment from a) a fuel controlled fire and b) a ventilation controlled fire, and c) realistic and ideal temperature profiles for heat sensors at different compartments within a multi-compartment structure.

complex. In a typical fire scenario, no prior knowledge is given to the location of the fire, the item that is being ignited, and the opening conditions for interior and exterior vents (i.e., doors and windows). For example, a window breakage or a damaged door can create an opening from a closed room allowing oxygen-rich fresh air to enhance the fire. An example is given in Figure 1b. Given the right amount of fuel, oxygen, and heat (known as the fire triangle), flashover occurs.

What makes the problem more complicated is that existing fire protection devices, such as heat sensors being placed at various locations within the structure, are likely to be destroyed due to flame and/or elevated temperature (i.e., ~ 150 °C to 250 °C and see Figure 1b for sensor failure) (NFPA 2002). If there is no temperature signal in the room of fire origin (refer to the green solid line in Figure 1b), no direct prediction about the potential flashover occurrence can be made. Although the remaining temperature signals from other compartments can be used as surrogates, since the interior opening conditions are unknown and it is not clear which temperature signals are useful (see the solid lines in Figure 1c in which the temperature variation across different compartments is substantial), the prediction will become highly uncertain. To the best of the authors' knowledge, no empirical expressions nor models exist that can efficiently correlate relationships between temperature from non-fire rooms and flashover in multi-compartment structures.

The second challenge is that temperature data in real fires for full-scale multi-compartment structures is limited. Firstly, it can be easily understood that flashover does not frequently happen (Ahren 2019). Even if it happens, data is difficult to collect, and the data quality is questionable because important information such as exact fire location, ignited items, and/or vent opening conditions might not be well documented in case of a fire accident. Secondly, temperature data associated with flashover in building structures are not available from any public data repository (i.e., Dua and Graff 2019). Lastly, physically conducting full-scale fire experiments involving flashover in a multi-compartment structure with living room, dining room, kitchen, bedrooms, doors, and windows is extremely costly and time-consuming. Given the data limitation and the numerical bottleneck, the development of a data-driven model for the prediction of potential flashover occurrence accounting for the realistic effect of fires and vent opening conditions in multi-compartment structures requires innovative approaches.

In this paper, we propose the utilization of the machine learning paradigm with the learning by synthesis approach to overcome these challenges. The main contributions of this work are summarized as follow:

- **Problem**: We engage a novel problem about fire fighting accounting for realistic fire and vent opening conditions in a multi-compartment structure. We propose to develop a flashover prediction model (P-Flash) which can be used as a potential solution to transform traditional fire fighting tactics from experience-based decision making to data-driven decision making to enhance situational awareness, operational effectiveness, and safety for fire fighting and to enable smart fire fighting (Hamins et al. 2015).
- **Algorithm**: We propose to use an attention-based bidirectional long short term memory to capture crucial relationships between temperature data and flashover conditions. The model is able to differentiate temperature information with higher significance and provide flashover prediction even when the temperature signal from the room of fire origin is completely lost.
- **Data**: We provide 5041 sets of synthetic temperature data accounting for fire scenarios with a wide range of fire and vent opening conditions within a single story residential building. The core difference between our data generation process and that found in other literature is that our fire simulation program is validated against real-life experimental data with identical settings. This validation process helps to ensure the reliability of our synthetic data. Data and code are available upon request.
- **Evaluation**: We evaluate P-Flash against real data obtained from 13 different full-scale fire experiments with the occurrence of flashover (Madrzykowski and Weinschenk 2019). Experimental results reveal that our

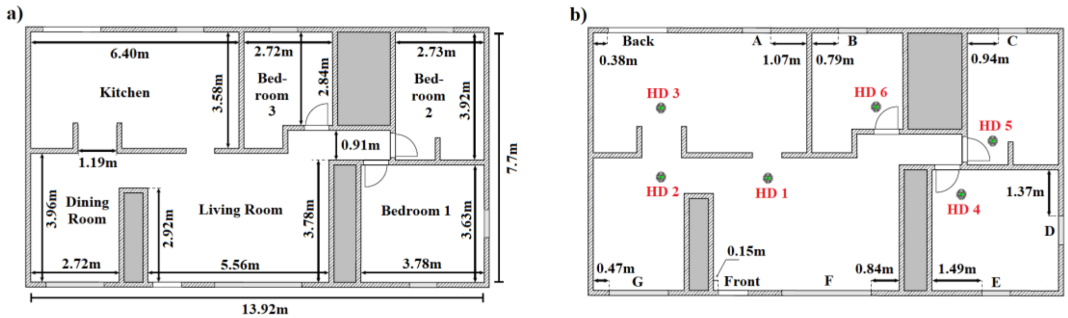

Figure 2: Plan view dimensioned drawing of a) the single story structure and b) vent openings with heat sensors (HD).

proposed method is feasible and hence has potential impact to real-world fire fighting.

Related Work

Flashover Prediction Models: Due to the technical complexity associated with the collection of temperature measurement for flashover conditions in full-scale experiments, research efforts primarily focus on single compartment structures. In the fire research community, correlation techniques relating air temperature and heat release rate (HRR) are typically being used for the estimation of flashover (Babrauskas 1980; McCaffrey et al. 1981; Deal and Beyler 1990; Richards et al. 1997; Overholt and Ezekoye 2012). The HRR can be understood as the rate of heat generation by a fire. Given an estimated HRR, the occurrence of flashover can be approximated. However, since these models are developed based on data obtained from small single compartments with approximately 16 m^2 in floor area and a single door-like vent, these models have limited applicability to multi-compartment structures.

Additional efforts are made to account for the geometric effect of flashover conditions (Yu et al. 2012; Zhang et al. 2014; Li et al. 2019; Kurzawski and Ezekoye 2020). Although their research outcomes provide substantial improvement for the development of flashover prediction models in multi-compartment structures, their models rely on assumptions that over-simplify the fire scenarios. Specifically, (i) all interior and exterior openings, such as doors and windows, are always assumed to be fully opened; (ii) fire locations are assumed to be at only one location; (iii) fire growth of burning items (i.e., how fast and how intensive the item is being combusted) is prescribed based on arbitrary functions without experimental validations; and (iv) most importantly, sensors being used to obtain the temperature signals are assumed to be ideal, meaning that the sensors will never fail. In contrast to the previous works, the realistic conditions involving items (i) – (iv) are considered in this present study. By doing so, our flashover prediction model is more suitable to provide flashover warnings to fire fighters for fire fighting in multi-compartments structures.

Generation of Synthetic Dataset using Simulation Models: The idea of using fire simulation models to generate synthetic data have been shown useful in recent studies such as fire detection in tunnel (Wu et al. 2020), structural fire protection design (Zhang et al. 2020), and hazard assessment (Lattimer et al. 2020) as it avoids the need of conducting costly experiments and facilitate parametric studies of a problem. For example, Wu and his coworkers (Wu et al. 2020) used a CFD model to generate detailed smoke and temperature data for different heat sensors at various locations with a wide range of fire and wind conditions. The advantage is clear. However, one potential concern is that they had never benchmarked and/or validated the model against full-scale experiments with similar fire and wind conditions. For that, it is uncertain if the synthetic data being generated from the model could capture the fire behavior correctly. In contrast, the reliability of our synthetic data is assured. Specifically, the synthetic data generated by our fire simulation model are benchmarked against experimental data (McKinnon et al. 2020) with identical settings. Therefore, we can quantify the accuracy of the fire simulation model in simulating the corresponding behaviors of fire and vent openings in a multi-compartment structure.

Multivariate Time Series Classification: Recurrent neural network (RNN) approaches, such as long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997), have achieved much success for various tasks in different scientific communities such as detection of mechanical failure (Guo et al. 2017), hurricane trajectory prediction (Alemany et al. 2019), understanding human communications (Zedeh et al. 2019), and early fake news detection (Liu and Wu 2019). Although LSTM is an efficient way to encode multivariate time series data, it processes inputs in temporal order in which its outputs tend to be mostly based on previous information without making full use of available information (Graves and Schmidhuber 2005). For the development of a flashover prediction model for situations similar to that of shown in Figure 1b, making use of all available information is crucial. Moreover, the standard LSTM may not have capabilities to discriminate data with higher significance, such as those temperature profiles (i.e., solid lines in red and

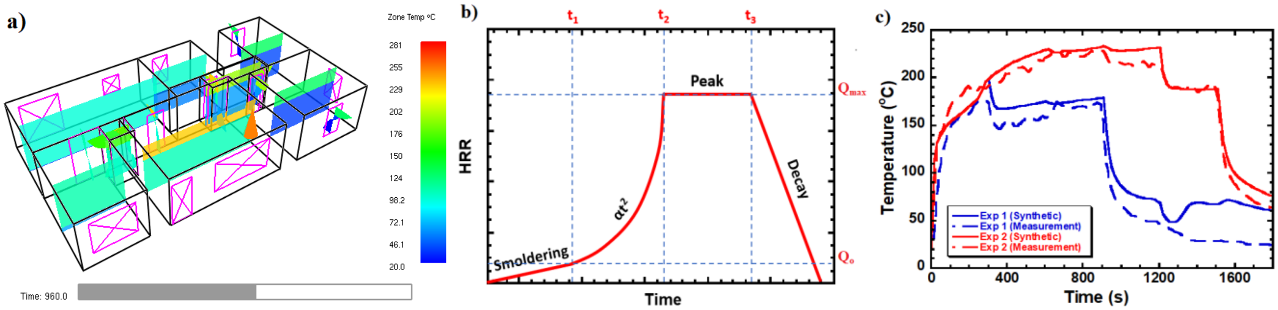

Figure 3: a) overview of a CFAST simulation run with a fire in the living room, b) standard t-squared fire HRR curve, and c) validation for Experiment 1 and 2 between CFAST results and measurements.

green) in Figure 1c. In this study, we will use the state of the art RNN architecture, namely bidirectional long short-term memory (BiLSTM) (Graves and Schmidhuber 2005) together with attention mechanism (Vaswani et al. 2017) to facilitate the learning of inherent patterns and complex relationships between temperature signals from non-fire compartments and flashover from the fire origin with realistic fire scenarios and arbitrary vent opening conditions.

Flashover in a Multi-Compartment Structure

Consider a single-story ranch structure as shown in Figure 2a. There are six different compartments: a living room, a dining room, a kitchen, and three bedrooms. The overall interior dimensions of the structure are roughly 13.92 m x 7.7 m with a ceiling height of 2.44 m. The detailed dimensions associated with each of the compartments are illustrated in Figure 2a. Since fire rarely occurs in bathrooms, bathrooms are not considered in current layout. For interior finish, the walls and ceiling are covered with gypsum wallboards and the floor is covered by cement board.

Figure 2b shows the relative position of vents and heat sensors in different compartments. For vents, there are two exterior doors (front and back), three bedrooms doors, a doorway that leads to the kitchen, and seven windows (A - G). For heat sensors, one heat sensor is located at each compartment, and they are about 0.02 m away from the ceiling. It is worth noting that this single story, traditional ranch style structure is selected because 90 % of residential buildings were built using this layout in the mid of 1950s (Madrzykowski and Weinschenk 2019). Currently, this structure remains the most popular style of home in 34 states across the United States (Mattern 2017). For that, the flashover prediction model developed based on this structure is expected to have substantial benefits for fire fighting across the U.S. Additional efforts accounting for the effect associated with different structure layouts is underway. Findings will be reported in future studies.

Synthetic Data Collection: CData (Tam et al. 2020) is utilized to execute simulation runs to generate the synthetic temperature data for a single item ignition fire with a wide range of fire and vent conditions. In general, CData is a Monte Carlo based sampler that uses CFAST[2] as the simulation engine. In this study, 5041 set of cases are considered, and it is consisted of about 1 million data points.

Three realistic conditions are taken into account in the data generation process, and they are 1) experimental validated fire growth of single burning items, 2) various fire locations, and 3) arbitrary opening conditions of vents.

Realistic Fire Growth of a Burning Item: Heat release rate (HRR) is the single most important variable in characterizing the fire growth of an item (Babrauskas and Peacock 1991). In order to obtain the HRR, experiments are typically performed, and Figure 3b shows the standard HRR curve. Specifically, this is the t-squared HRR curve that is used to describe the overall burning behavior of a single item in the fire research community. As shown in the figure, a burning item might experience four different fire growth stages: smoldering, t-squared growth, peak, and decay. Flashover usually happens in approximately between the t-squared growing stage and the peak stage. For that, experimentally validated HRR curves are crucial in capturing the precise burning behavior of an item such that the corresponding fire growth can be matched closely to actual fire scenarios. Four items, including a flaming chair, smoldering chair, polyurethane foam mattress, and cotton based mattress, are considered in this study (Reneke et al. 2019). The selection of these items is due to the fact that these items represent the largest portion of first ignited item in home fires (Ahrens 2017).

[2] CFAST (Peacock et al. 2015) is a fire simulation program that divides compartments into two zones. Each zone includes a gas mixture/soot medium bounded by a ceiling or a floor, and four surfaces. Conditions of each zone are assumed to be uniform. When there is a fire, a hot layer will form and the medium can be divided into an upper layer and a lower layer. If the fire persists, the upper layer increases in depth and the temperature will rise. When openings exist, there will be natural flow through the openings allowing air exchange between different compartments and zones. Figure 3a shows a simulation case for the single-story ranch structure with a fire in the living room.

Table 1 provides the table for the summary of HRR parameters associated with the four different items.

Fire location and Vent Openings: A fire can be initiated at the center of either one of the six different compartments in each simulation. Since the fire simulation model being used is a zone model, the exact location of the fire does not have any significant impacts to the resulting temperature (if the fire is not attached to any walls or corners). In the current dataset, the number of fire cases is distributed evenly for the six different compartments (i.e., about 840 cases for each compartment). For vent openings, all doors and windows within the structure, except the front door, are randomly selected to be either opened or closed at the beginning of a simulation run. For the front door, it can be opened at any time during a run. This arrangement accounts for the effect of different opening vents. In this current study, each of the vents is assigned to be opened for 60 % of the total cases. The value is chosen because we want to facilitate flashover conditions.

Validation with Experimental Data: In order to make sure that CData can be used to generate realistic temperature data for different fire scenarios, validation is carried out. Specifically, temperature measurements obtained from two full-scale experiments reported in (McKinnon et al. 2020) with a fire initiated in the living room within the single story residential structure are used to benchmark the synthetic data. The fire location and the HRR of the burning item for the two tests are the same. Yet, opening conditions of each of the vents are different. The details of the opening time for each vent is provided in table attached to Table 2. It is worth noting that natural gas burners are used in these experiments. The reason is that the HRR of the fire can be fully controlled by regulating how much natural gas is being burned. By doing so, we can be assured that the simulation conditions and the experimental conditions are identical.

Figure 3c shows the temperature measurements (dash lines) and the synthetic temperature data (solid lines) from the living room sensor for the two experiments. The overall agreement is great. It can be seen that the magnitude and trend of the temperature profiles matches the experimental data for different vent opening events. This observation indicates that CFAST, the simulation engine of CData, is capable of capturing both the corresponding effect of fire and vent openings in the single story multi-compartment structure. In terms of uncertainty, the absolute root mean squared error is about 30 °C and 10 °C for Exp 1 and Exp 2, respectively. Therefore, it can be said that the generated data is reliable.

Algorithm

Given the synthetic set of temperature data, our model will have to be able to carry out the following two tasks: 1) to relate complex data behavior to flashover conditions accounting for the effect of different fire and vent opening conditions and 2) to discriminate data with higher significance (see Figure 1c) and encode contextual information.

Table 1: HRR parameters (Reneke et al. 2019; Kim and Lilley 2002).

Items	Q_o (kW)	Q_{max} (kW)	t_1 (s)	t_2-t_1 (s)	t_3-t_2 (s)
Flaming Chair	10 - 30	270 - 3500	150 – 1250	90 - 600	200 – 400
Smoldering Chair	10 - 20	250 – 2500	5000 – 11000	70 - 500	200 – 400
Mattress (foam)	20 – 55	2200 – 4700	150 – 1250	200 -600	150 – 300
Mattress (cotton)	15 - 40	150 – 820	150 – 1250	30 – 1400	250 – 550

Temperature Signal Learning: In order to overcome the challenge associated with the 1st task, we propose the use of bidirectional long short-term memory (BiLSTM) (Graves and Schmidhuber 2005). Figure 4a shows the overall model architecture. It can be seen that for a temperature signal: $S = (s_1, s_2, \dots, s_\tau)$ and a time step i, BiLSTM includes a forward hidden state $\overrightarrow{h_\iota}$ and a backward hidden state $\overleftarrow{h_\iota}$. In this study, since we are interested to capture the complete behavior for temperature signals, we only make use of the last hidden state of $\overrightarrow{h_\tau}$ and $\overleftarrow{h_\tau}$. As shown in the figure, concatenation is applied to yield $h_\tau = [\overrightarrow{h_\tau}, \overleftarrow{h_\tau}]$ to encode temperature behavior with flashover conditions.

Sensor-Wise Self-Attention: In order to enhance the learning capability of the model in discriminating temperature signals with higher significance for more reliable prediction (i.e., neglecting bedroom 2 temperature signal in Figure 1c), we utilize a self-attention mechanism to model sensor-wise relation. For that, we will be able to extract the contextual temperature information of all compartments within the structure. It is believed that the contextual information can contribute to provide more accurate flashover predictions.

As shown in Figure 4b, our model takes the temperature signals from all compartments ($\{S_1, \dots, S_N\}$, $N = 6$) as inputs. Using the BiLSTM, we obtain the hidden state of temperature behavior (h_τ) for each signal. We then feed them into a sensor-wise self-attention module for sensor relation

Table 2: Event sequence.

Event	Exp 1	Exp 2
Front Door Open	300 s	1200 s
Back Door Open	1275 s	1860 s
Window A Open	1260 s	1845 s
Window B Open	1245 s	1830 s
Window C Open	1230 s	900 s
Window D Open	1215 s	Closed
Window E Open	600 s	600 s
Window F Open	1200 s	1815 s

modeling. Specifically, the attention weight (α_{ij}) of each pair of sensor signals (S_i, S_j) is determined based on the interaction of their modeled temperature behavior (h_τ^i, h_τ^j):

$$a_{ij} = {h_\tau^i}^T h_\tau^j \tag{1}$$

$$\alpha_{ij} = \frac{\exp(a_{ij})}{\sum_{k=1}^{N} \exp(a_{ik})} \tag{2}$$

To obtain the contextual temperature information that captures the temperature behaviors of all compartments. We extract context features based on the learned attention weights. For a signal S_i, we compute its context feature as:

$$e_i = \sigma(W_e h_\tau^i + b_e) \tag{3}$$

$$c_i = \sum_{j=1}^{N} \alpha_{ij} e_j \tag{4}$$

where σ is the activation function, and W_e and b_e are the parameters of a dense layer for further encoding temperature behavior. We attain the final feature representation u_i' for S_i after applying one dense layer on the concatenation of its context feature and encoded feature: $u_i = [c_i, e_i]$ such that:

$$u_i' = \sigma(W_c u_i + b_c) \tag{5}$$

We compute the representation for all temperature signals by the same manner to acquire the overall representation of the whole structure: $\mu' = [u_1', \ldots, u_N']$. This feature representation is used to predict whether there is a flashover occurrence within the coming x seconds based on the available temperature signals.

Evaluation

Experimental Settings: Each synthetic fire experiment has six temperature signals (S) and each signal is corresponding to a compartment (i). The temperature signals from the compartment are denoted as $S^i = (s_0^i, s_{15}^i, \ldots, s_T^i)$ where s_0^i and s_T^i are the first and the last temperature for an experiment, respectively, and T is the total duration. The sampling interval for all temperature signals is 15 s and this is selected to facilitate the data generation process. In total, there are 5041 synthetic fire experiments/events.

Sliding window is applied and instances are constructed. An instance from a fire event is formulated as $I_k = \{S_k^1, \ldots, S_k^6\}$ where $S_k^i = (s_k^i, \ldots, s_{k+w}^i)$ with k to be the first time step of the sliding window and w to be the window size. Accounting for the sensor limit, we adopt the sensor failure threshold of 250 °C from (NFPA 2002). Given the threshold, the sensor failure moment (T_b^i) for signal S^i can then be determined. If time $t \geq T_b^i$, s_t^i is replaced by a value of 0 °C, representing a loss of sensor signal. A masking layer is applied to neglect the zero values. Extracting all the I_k from all fire events, the instance set $\{I_0^1, \ldots, I_k^{5041}, \ldots\}$ is obtained.

Our task is to predict whether flashover will occur within the next x seconds based on the temperature data in I_k^e. In our experiment, we evaluate the models when $x = 30$ s and $x = 60$ s. These values are chosen with careful consideration about the response time in actual fire fighting (Dunn 2015). Due to movement limit (i.e., crawling to avoid excessive heat from ceiling), it will take 10 s for fire fighters to travel for approximately 3 m in a fire scene. For that, predictions ahead of flashover occurrence is crucial in order to allow the fire fighters to get away from the dangerous compartments or find shelters. Therefore, we will examine our model performance for $x = 30$ s and $x = 60$ s.

Each instance is labeled to form our data samples, and the instance is either labeled as Flashover or Non-Flashover based on its future temperature value. In our study, we take 550℃ to be the threshold of the onset of flashover conditions. In the current dataset, we have data imbalance for samples associated with Flashover and Non-Flashover. It can be understood that when $x = 30$ s, we only have two Flashover samples in one fire event (i.e., I_{f-15-w}^e and I_{f-30-w}^e where f is the flashover moment for event e). And when $x = 60$ s, the number of Flashover samples is four for one fire event (i.e., I_{f-15-w}^e, …, I_{f-60-w}^e). However, there are many Non-Flashover samples. In order to overcome the data problem, we first take all the Flashover samples and randomly select two (four) Non-Flashover samples for $x =$

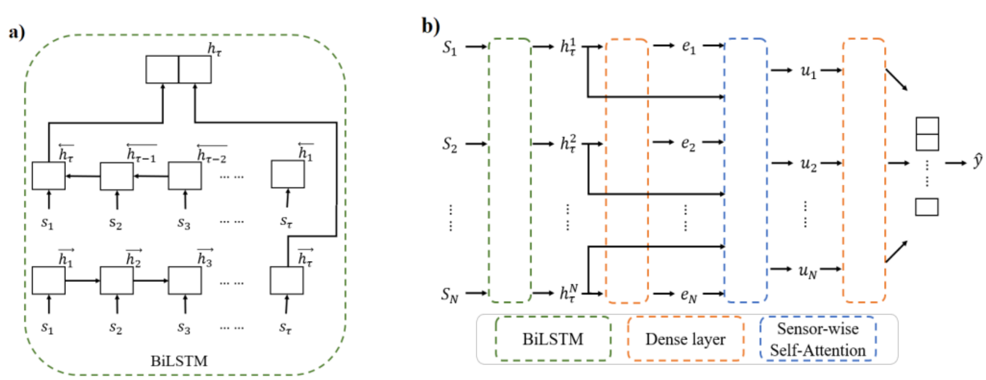

Figure 4: a) Model architecture of BiLSTM and b) BiLSTM with sensor-wise self-attention.

Table 3: Performance of flashover prediction.

x	Model	Acc.	Prec.	Rec.	F1
60s	BiLSTM	81.80%	86.88%	74.90%	80.45%
	BiLSTM-Attention	86.46%	84.54%	89.24%	86.82%
30s	BiLSTM	78.17%	76.94%	80.46%	78.66%
	BiLSTM-Attention	81.75%	79.47%	85.62%	82.43%

30s (60s) from each fire event. These samples are used to form our final dataset. In this experiment, we have 20164 and 40328 data samples (from 5041 fire events) for the experiment of adopting x as 30s and 60s, respectively.

For training and testing, we randomly split the data samples to form subsets for training, validation, and testing based on the fire events. Specifically, a set of 504 fire events worth of data samples are assigned to both validation set and testing set, respectively. The data samples from the rest of the 4033 (5041 – 2*504) fire events are given to the training set. The data proportion for training and testing process are identical to both $x = 30$ s and $x = 60$ s.

Model Configurations: We set the dimension of both the forward and backward LSTM as 28. The output dimension of our BiLSTM module is 56. We adopt 28 and 16 as the output dimension of the first and second dense layer in our model. Dropout is applied in the network with a dropout rate of 0.2. In order to evaluate the efficiency of the proposed sensor-wise self-attention module, we compare the performance of the BiLSTM model with attention (refer to it as BiLSTM-Attention) and the BiLSTM model without attention (refer to it as BiLSTM) in our experiments.

Experimental Results: Table 3 shows the model performance for flashover prediction made in 30 s and 60 s. Based on the accuracy and F1 scores, it can be shown that the proposed attention-based BiLSTM outperforms the original BiLSTM. It is worth noting that the attention-based model also yields a significantly better recall score, indicating the benefits of including the sensor-wise self-attention mechanism. This is extremely important for life saving purpose in fire events.

As shown in Table 3, the overall performance for prediction of flashover occurrence with x = 60 s is generally better. One possible reason is due to the fact that it has a larger set

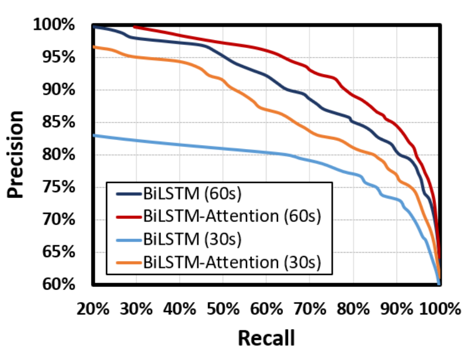

Figure 5: Precision and recall curves.

of training samples. For future work, we will keep collecting data to train a better prediction model for both scenarios.

Precision-recall curves are illustrated in Figure 5. In real-life application, we would like to maximize the value of true positive for prediction of flashover occurrence with minimal or even zero false positive to avoid disturbance to fire fighters. As shown in Figure 5, it is observed that the attention-based model can obtain a precision value of approximately 85% with the recall value being above 90% (for 60 s). Generally, our proposed attention-based models (both 60 s and 30 s) can achieve higher recall with higher precision. The overall performance of the attention-based model is therefore more robust than those without the attention mechanism. The success of the attention-based model is built upon its ability of determining the relation of different sensor signals for different vent opening conditions.

Figure 6 illustrates the learned attention weights between sensor signals in fire origin room and other compartments: kitchen (K), dining room (D), living room (L), and bedroom 1 to 3 (B1, B2, B3), for two door opening conditions: all opened denoted as Open and all closed denoted as Close. Our attention-based model can discover the spatial relation between sensor signals from different compartments. For instance, when fire occurs in kitchen, the signal of dining room and living room are determined as the most discriminating surrogate signals by the model (Figure 6a). And those from dining room and kitchen are taken as the most useful surrogate signals, when it comes to predicting flashover in living room (Figure 6b). These consist of the spatial relations of dining room, kitchen, and living room. The sensors placed in these three rooms are very close to each other. Hence, the model can predict flashover in one of them via modeling signals from the other twos, even when the doors are closed. On the other hand, the signals from dining room and kitchen are barely important for our model when fire occurs in bedroom 1, regardless of the door opening conditions (Figure 6c). This also agrees with their spatial relations

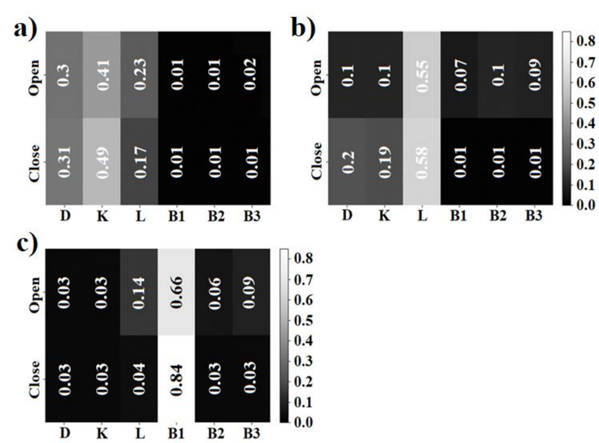

Figure 4: Learned attention for (a) Kitchen, (b) Living room, and (c) Bedroom 1, under different door opening conditions.

Table 4: Key information for each of the experiments.

Exp #	Fire Location	Ignited item	Ventilation
1	Living Room	Sofa	All Vent Closed
2	Living Room	Sofa	All Vent Closed
3	Living Room	Sofa	Front Door Open
4	Living Room	Sofa	Front Door Open
5	Living Room	Sofa	Front Door and Bedroom 3 Window Open
6	Kitchen	Cabinet	All Vent Closed
8	Kitchen	Cabinet	All Vent Closed
10	Kitchen	Cabinet	Front Door Open
11	Kitchen	Cabinet	Front Door Open
7	Bedroom 1	Mattress	All Vent Closed
9	Bedroom 1	Mattress	All Vent Closed
12	Bedroom 1	Mattress	Front Door and Bedroom 1 Window Open
13	Bedroom 1	Mattress	Front Door and Bedroom 1 Window Open

that the sensors in dining room and kitchen are farer away from that in bedroom 1.

Moreover, different door opening conditions may also influence the relations of the sensor signals. Our attention-based model can also capture that. For example, our model determines that signal in living room has stronger relationships with that of bedroom 1, 2 and 3 when all the doors are opened, compared to the situation of closing all the doors (Figure 6b). Also, our model can find that for predicting flashover in bedroom 1, signals of living room, bedroom 2 and 3 are more useful when all the doors are opened than closed (Figure 6c).

The learned attention weights indicate that our attention-based model can successfully determine the relationships between different sensor signals under different door opening conditions. This results in extracting the most discriminating signals and contextual information. Based on that, a more reliable flashover prediction can be provided.

Towards Prediction in Real Fire Event: Given a flashover prediction model trained based on synthetic data (BiLSTM-Attention with 30 s), it is necessary to examine its performance against real-life fire scenarios. In this evaluation process, 13 sets of full-scale experiments reported in (Madrzykowski and Weinschenk 2019) are utilized. The building structure is identical to that of shown in Figure 2a. In these experiments, a single item is first ignited in either living room, kitchen, or bedroom 1. Temperature measurements are obtained and videos from thermal image cameras are recorded. Important information for each of the experiments is summarized in Table 4. As shown in the table, although a number of tests are repeated, the fire growth is rather different. It should be noted that our model never sees any of the experimental data.

Due to the nature of the experiments, data associated with flashover and non-flashover conditions are imbalanced. In order to provide a fair comparison, the model performance is assessed based on 4 selected instances. With that, the model will make predictions about 15 seconds (Instance I) and 30 seconds (Instance II) prior to the flashover occurrence. These two instances are labeled as true for flashover occurrence. The exact time of flashover is obtained from the experimental data. The Instance III and IV are the non-flashover instances.

Table 5 shows the prediction accuracy for the instances associated with all 13 experiments and the 3 individual test series. It can be seen that the model performance for kitchen fire and bedroom 1 fire associated with either Instance I or II is substantially different. Fundamentally, this deficiency is primarily due to the fact that the HRR curves obtained based on standard experiments do not account for the enclosure effect (Ramesh and Venkateshan 1999). In principle, the high temperature environment surrounding the ignited item will enhance its pyrolysis process (Garrido and Font 2015), increasing the release rate of combustible gases, and accelerate the burning of an item. This combustion process is not being captured in current experiments[3] for HRR determination. For that, although experimentally validated HRR curves for foam mattresses is used during the data generation process in this study, the corresponding temperature behavior is substantially different. The rate of increase of temperature observed from the full-scale experiments is nearly double as compared to that of seen in our training data. For the kitchen fire, since wooden materials are the primary burning items, they have less influence with the enclosure effect. For that, the experimental temperature data are within the range of our synthetic data. Therefore, the flashover prediction is excellent. This observation is encouraging, and this is because a reliable flashover prediction model can be built even with synthetic temperature data if correct HRR curves accounting for the enclosure effect are applied. Also, it is believed that when the new data is available, the model performance for the flashover prediction model can be greatly enhanced.

Table 5: Model performance against real data.

	Instance I	Instance II	Non-Flashover
All	64%	54%	89%
Living room	80%	60%	80%
Kitchen	100%	100%	100%
Bedroom 1	25%	0%	100%

Conclusion

In this paper, we present the development of a flashover prediction model for a multi-compartment structure using an attention-based BiLSTM with validated synthetic temperature data. This is the first work in which the realistic effects of fire locations, burning behavior of ignited items, vent

[3] For standard experiments, an item is ignited in a room temperature environment. Therefore, the pyrolysis process is sustained due to its own combustion and the enclosure effect due to room temperature is relatively small.

opening conditions, and data limitation due to sensor failure are being accounted for at the same time. Our model achieves promising performance. For synthetic datasets, it has the accuracy of ~ 86 % and ~ 82 % with the F1 score of ~ 87 % and ~ 82 % for prediction of flashover occurrence within the next 60 s and 30 s, respectively. The model performance is also tested against real data with flashover conditions in full-scale fire experiments. The overall accuracy for prediction of flashover occurrence is ~ 75 %. In the future, we will carry out physical experiments to account for the enclosure effect in HRR determination. Also, we are interested in developing a more generic flashover prediction model that can be used in any single story structure layout. It is believed that the flashover prediction model can help to save lives by enhancing situational awareness, operational effectiveness, and safety for fire fighting and enable smart fire fighting.

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