Detecting Firefighter’s Thermal Risks in a Commercial Building Structure Using Machine Learning

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Abstract. A multi-input and multi-output (MIMO) machine learning model is developed to simultaneously detect firefighter’s thermal risks in a commercial building. A total of 2 000 numerical experiments with a wide range of fire and ventilation scenarios are carried out using Fire Dynamics Simulator. Temperature data is obtained from sensors over a simulation duration of 900 s with a 5-s time step. A dataset consisting of 242 000 instances is constructed. The instances are labelled by four thermal operating conditions and are pre-processed for the purpose of training, validating, and testing a machine learning model. Model performance of the MIMO model is provided, and it is benchmarked against typical multi-input and single-output (MISO) machine learning models in terms of accuracy and computation time. Results show that the MIMO model can provide the same accuracy as MISO in detections of thermal operating conditions at multiple locations simultaneously but 10 times faster in computation than MISO. MIMO achieves almost the same recall and precision as MISO except for two locations with binary classes caused by fluctuations in the labels. This research demonstrates the potential of using machine learning methodologies to develop practical firefighting applications which can, in turn, enhance firefighters' situational awareness and improve their safety measures during firefighting and/or carrying out search-and-rescue in a large commercial building structure.

1. Introduction

Firefighters are exposed to thermally hazardous environments during emergency responses, placing them at significant risk of injury and even death. Recent statistics from the National Fire Protection Association (NFPA) show a total of 65 650 firefighter injuries occurred in 2022, experiencing an 8% increase from the previous year’s 60 750. Furthermore, 2022 marked the highest number of on-duty fatal firefighter injuries since 2013, with 96 reported deaths [1]. These alarming statistics highlight the dangers that firefighters face during emergency responses (i.e., firefighting and search-and-rescue), where they undertake strenuous tasks amidst intense heat exposure. The thermal risks include not only burn injuries, but prolonged heat exposure also exacerbates physiological stress, increasing the likelihood of sudden cardiac death (SCD). SCD accounted for approximately 38% of firefighter fatalities in 2022. Compounding these risks, firefighters navigate obstructive spaces while wearing heavy protective gear, weighing over 14 kg. These hazardous conditions significantly elevate the likelihood of fatal and near-fatal sudden cardiac events [2]. Given these challenges, enhancing the overall safety measures for firefighters is critical in saving lives and reducing economic losses.

Firefighters’ thermal risk is measured by thermal loads. Efforts have been made to study fire risk by investigating protective clothing [3], equipment [4], search and rescue strategy [5], structural performance [6], fire following earthquakes [7], fire in process industry [8] and wildfires [9]. These studies have set the groundwork for establishing thermal operating conditions (TOC) thresholds in a fire scene. Investigations conducted within full-sized residential structures have aimed to quantify the thermal loads experienced by firefighters across different roles. Furthermore, comprehensive full-scale tests have been conducted within residential settings, considering factors like ventilation, suppression techniques, and timing [4-5,10]. Thermal exposure assessments were quantified through temperature and heat flux measurements. Based on [10], firefighter's TOCs were classified into three categories: Routine (20 ℃ to 72 ℃, 1 kW/m^2 to 2 kW/m^2), Ordinary (72 ℃ to 200 ℃, 2 kW/m^2 to 12 kW/m^2), and Emergency (>200 ℃, >12 kW/m^2). Building upon this framework, researchers from Underwriters Laboratories expanded the TOC into six categories: Routine (20 ℃ to 72 ℃, 1 kW/m^2 to 2 kW/m^2), Ordinary I (72 ℃ to 200 ℃, 2 kW/m^2 to 7 kW/m^2), Ordinary II (72 ℃ to 200 ℃, 7 kW/m^2 to 12 kW/m^2), Emergency I (200 ℃ to 260 ℃, 12 kW/m^2 to 15 kW/m^2), Emergency II (260 ℃ to 600 ℃, 15 kW/m^2 to 50 kW/m^2), and Emergency III (>600 ℃, >50kW/m^2) [5].

While these criteria offer valuable insights into assessing firefighter's thermal risk, it is worth noting that previous studies have primarily focused on fire risk prediction in a single location at a moment in time which is not applicable to real fire applications [5,11]. In real scenarios, the firefighters are moving around in the building structure. Therefore, the firefighters' exposure to thermal hazards is changing with time and their locations. A brute-force approach can be used as a solution to run the multiple-input and single-output (MISO) model multiple times to obtain predictions at various locations [11]. However, this approach is not practical because it does not provide a complete picture of the thermal hazards in a large commercial building structure. Indeed, a model that can detect the fire risk/TOC of firefighters in situ in real-time and provide multiple outputs of TOC anywhere in a building is lacking. In real fire scenarios, firefighters react to thermal risks based on their experience and knowledge. Depending solely on experience is not a reliable method for firefighters on a dynamic fireground, particularly for less-experienced firefighters who may lack sufficient practical firefighting knowledge. With the advancements in sensor technology, continuous collection of data from building sensors is possible. However, during an emergency response, unprocessed information is not helpful for the incident commanders and the firefighters. Simple and straightforward actionable information is needed for firefighters to enhance their situational awareness in hazardous environments with extreme thermal loads. Therefore, developing a model that can provide the incident commanders/firefighters with detections of TOC simultaneously at different locations will inform the incident commanders/firefighters of their thermal exposure and guide their operations and movements.

As machine learning (ML) methodologies have gained prominence in fire protection, they have been increasingly applied for detecting temperatures and possible flashover within building fires and guiding firefighting strategies [11]. By leveraging real-world data, advanced ML algorithms can accurately and efficiently forecast extreme fire events such as flashovers [11], thus empowering firefighters with enhanced situational awareness and enabling them to take proactive measures to mitigate thermal hazards. Building upon previous research, this study endeavors to develop an ML model that can provide detections of TOC at any required locations simultaneously. To achieve this, synthetic fire data is generated using the Fire Dynamics Simulator (FDS), incorporating diverse fire sizes and ventilation scenarios within a commercial building layout that is compliant with the International Building Code (IBC) and NFPA 101 Life Safety Code (LSC). Subsequently, synthetic data is utilized to train and evaluate the ML model. Finally, we will compare the performance of our multi-input and multi-output (MIMO) model against that of a MISO model. The proposed model aims to establish a framework for detecting firefighters' TOC simultaneously at any location, thereby being able to provide a complete picture of the fire scene and improve firefighters' situational awareness.

2. Methodology

The objective is to develop a new machine learning model capable of capturing spatial dependencies to detect TOC at any desired location within a commercial building during a fire. The proposed methodology includes: 1) systematically generating synthetic temperature data with the consideration of various fire scenarios; 2) pre-processing the synthetic temperature data to construct data samples; and 3) developing the

MIMO machine learning model to detect firefighter's TOC and compare the performance of MIMO with MISO.

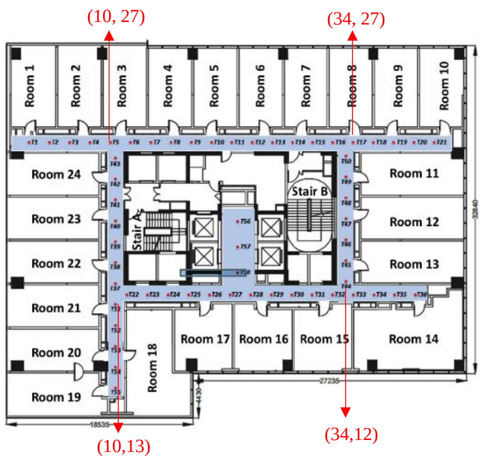

Figure 1. Building layout.

Figure 2. Code analysis of the layout.

2.1. Generating data

To develop a reliable ML model for assessing firefighter's thermal risk, it is important to have a robust dataset that accurately reflects real-world fire scenarios. Our objective is to determine the firefighter's TOC based on 59 temperature readings (as shown in red dots of Figure 1) with a spacing of 2 m gathered from various locations near the ceiling at a height of 2.18 m relative to the floor. Sensitivity analysis of sensor spacing shows that the results converged with a sensor spacing of 2 m. Given the intricate nature of fire behavior within large commercial buildings, particularly those featuring diverse room layouts and long corridors, the use of FDS is essential to obtain high-fidelity data. Although FDS models are too computationally intensive to be employed in real-time applications, they can be utilized to generate fire data, which in turn can be used to train surrogate models. Our proposed method entails employing FDS to simulate a variety of fire scenarios within a commercial building structure, such as a hotel layout depicted in Figure 1 (representing a floor plan from a multi-story commercial structure). Temperature data has been collected from sensors at four different heights: 0.6 m, 1.1 m and 1.9 m above the floor and the heights are selected based on anticipated firefighter movement paths. As a proof of concept, 9 targeted locations are selected: 1) (10,27,0.6), 2) (10,13,0.6), 3) (10,27,1.1), 4) (34,27,1.1), 5) (10,13,1.1), 6) (34,27,1.9), 7) (34,12,1.9), 8) (10,27,1.9), and 9) (10,13,1.9) as indicated in red in Figure 1. Note the numbers in (10,27,0.6) represents the geometric coordinates (x, y, z) of the targets in the FDS model. A ML model is developed to simultaneously detect the TOC at these locations. The model inputs include temperature obtained from sensors near the ceiling. The output is the TOC of firefighters in a specific location at different heights.

The building layout follows the 2018 edition of the IBC [12] and 2015 NFPA 101 LSC [13]. The important egress requirements for the hotel building structure based on the IBC and the LSC are separation distances between exits, travel distance to exits, common paths of travel, and maximum dead-ends. The estimated distances have an uncertainty of 0.5 m.

For this building layout, the longest diagonal distance is approximately 58 m (see blue line in Figure 2). The one-half and one-third of the longest diagonal distances are 29 m and 19 m, respectively. Based on an approximate separation distance of 20 m (see purple line in Figure 2), the exit separation is acceptable for a building with automatic sprinkler protection (ASP) but not for one without ASP.

The impact of common paths of travel and dead-end requirements are also required to be assessed. The lengths of common travel paths and dead ends are approximately 10 m (see red lines in Figure 2). This value is acceptable for buildings with ASP, but it does not satisfy the dead-end requirement for buildings without ASP.

Based on the analysis shown in Figure 2, the longest travel distance from an exit is approximately 26 m (see orange line in Figure 2) and the longest distance to a guest room door to an exit is 11 m (see green line in Figure 2). These two values are acceptable for both buildings with and without ASP. The floor layout would be acceptable for a building with ASP under both the 2018 edition of the IBC and the 2015 edition of the NFPA 101 LSC.

A total of 2000 numerical experiments have been conducted to include a range of fire sizes and ventilation scenarios (see Table 1). Assuming a threshold limit of 150 °C for window breakage due to thermal exposure [11], various temperature conditions have been generated by considering a diverse set of fire growth rates, as shown in Table 2. The temperature collected from 59 sensors will be used as inputs and the temperatures collected from the 9 different locations will be used as outputs. These data are used to train the machine learning model.

Table 1. Variations in parameters.

Parameters in Room 24	Distribution	Range
Peak HRR	Uniform	[2675 kW – 9790 kW]
Time to open the door	Uniform	[30 s – 180 s]
Threshold of window breakage	Constant	150 °C [11]

Table 2. No. of simulations for different fire growth rates.

Fire growth rate	No. of simulations	Time to reach peak HRR (s)
Slow	200	[1546 – 1938]
Medium	750	[733 – 969]
Fast	750	[386 – 484]
Ultra Fast	300	[193 – 242]

2.2. Pre-processing the data

After generating the data, pre-processing such as cleaning the data, removing the outliers, and splitting the data will be conducted to obtain the training, validation, and testing datasets for the ML model development. Since firefighters require simple and straightforward actionable information, firefighter thermal risk is considered a multi-class classification problem with thermal operating classes shown in Table 3.

Instances are constructed to develop the model. The simulation time of the numerical modeling is 900 s with a time step of 5 s, resulting in 181 time-steps of FDS outputs per fire scenario. With time window of 300 s (60 time-steps of FDS outputs per instance), 122 (=181-59) instances are obtained in each numerical experiment. A slide window of 300 s with a sample interval of 5 s is applied to anticipate the physical limits associated with real-time applications (i.e., sensor memory capacity and data transmission).

The instances are labeled based on the thermal operating classes in Table 3. Among the 9 target locations, 7 locations only observe binary classes (Routine and Ordinary I) and 2 locations observe three classes (Routine, Ordinary I, and Emergency I). With a sample interval of 5 s, a total of 244 000 (2000 numerical modeling×122 samples per numerical modeling) are constructed.

Finally, the collected data samples are divided into two parts: 80 % of data is used to train and validate the model and 20 % of the data is used to test the performance of the model. For that, the training, validation, and testing have 156 160, 39 040, and 48 800 data samples, respectively.

2.3. Developing the ML model

We apply convolutional neural networks to develop the model. Using the Adam optimizer [14] with a learning rate of 5e-5, the neural network weights and biases are updated accordingly. A batch size of 256 is used to facilitate the training process. Binary cross-entropy and categorical cross-entropy [15] are used to measure the loss for binary classifications and multi-class (three) classifications, respectively. The validation loss is used to avoid overfitting. Performance metrics including accuracy, recall, and precision are used to evaluate the performance for the testing subset.

Table 3. Firefighter's thermal operating classes.

Thermal operating classes	Temperature range (℃)
Routine	[20, 72]
Ordinary I	[72, 200]
Emergency I	[200, 600]
Emergency II	>600

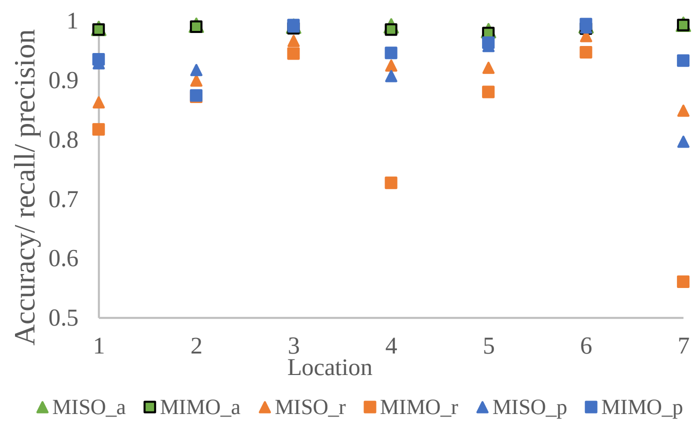

Figure 3. Performance of MISO and MIMO: a for accuracy, r for recall and p for precision.

Table 4. Accuracy/recall/precision of MISO and MIMO for locations with three classes.

MISO	Location 8			Location 9		
Class	Routine	Ordinary I	Emergency I	Routine	Ordinary I	Emergency I
Recall	98.9 %	98.4 %	95.5 %	99.7 %	97.5 %	42.3 %
Precision	98.2 %	97.0 %	99.3 %	97.2 %	96.6 %	99.3 %
Accuracy	97.9 %			96.9 %		
MIMO	Location 8			Location 9		
Class	Routine	Ordinary I	Emergency I	Routine	Ordinary I	Emergency I
Recall	99.3 %	97.9 %	94.1 %	99.8 %	96.2 %	51.3 %
Precision	97.3 %	96.6 %	99.6 %	95.9 %	97.1 %	98.5 %
Accuracy	97.5 %			96.6 %		

3. Results and discussion

The model performance for detection of firefighter's TOC with MISO and MIMO for various locations is shown in Figure 3 for the 7-location with binary classes (Routine and Ordinary I) and Table 4 for 2-location with three classes (Routine, Ordinary I and Emergency I). For locations with binary classes, the accuracy for the two models is nearly identical, indicating MIMO can achieve accuracy as high as MISO while MIMO can make predictions simultaneously for 9 locations. The recall and precision of the two models are approximately the same except for locations 4 and 7. This is caused by significant fluctuations in the labels which make it difficult for MIMO to classify Routine and Ordinary. The ratio of 'Routine' class to 'Ordinary I' class in MIMO is much lower than that in MISO. For 2-location there are three classes, the accuracy for MISO and MIMO is nearly the same, about 97 % for location 8 and 96 % for location 9. Recall and precision from the two methods do not show much difference, but for location 9, the recall of Emergency I by MIMO is higher than that by MISO since the label of 'Emergency I' in location 9 is much lower than that in location 8. The computational time for one prediction from MISO is about 6.4E-5 s and it is about 8.1E-6 s for MIMO. The fast detection of thermal risks at multiple locations would inform firefighters of real-time hazardous conditions. This approach can be expanded to predict the duration of firefighters' operation in the hazardous conditions and relocate or withdraw firefighters from the fire scene to help reduce the likelihood of fatal and near-fatal sudden cardiac events due to prolonged thermal exposure [4].

4. Concluding remarks

This study proposes a MIMO model that can detect firefighter's thermal risk at multiple locations with temperatures at the ceiling in commercial buildings as inputs. The model is trained with synthetic data which is generated from FDS. Data-preprocessing is conducted to clean the data and construct the data samples. Convolutional neural network is applied to develop the model. The performance of the model is measured with metrics including accuracy, recall and precision. Results show that MIMO achieved approximately the same accuracy for all locations as MISO. Recall and precision for MIMO and MISO are almost the same except for two locations with binary classes caused by data imbalance. We will have an accurate and reliable MIMO model that can detect multiple firefighter's thermal risks as MISO but increase computational speed by almost 10 times. The model can be further extended to detect the thermal risk of firefighters under thermal exposures and choose the optimal path which can significantly improve firefighters' situational awareness.

5. References

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