Detecting Firefighter’s Tenability Utilizing Machine Learning

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Abstract

The proposed research leverages machine learning to detect thermal operating classes and improve the tenability of firefighters in a commercial building. A total of 2000 simulations are run with Fire Dynamics Simulator to collect temperature from heat detectors. The total simulation time is 900 s with a time step of 5 s. A total of 244,000 instances are obtained from FDS simulations. The temperatures obtained from FDS are later processed for training, validation, and testing of a machine learning model with a ratio of 69:14:17. The machine learning model is fine-tuned. A multiple-input and single-output machine learning framework with time-series temperature information is developed to detect firefighter’s thermal tenability, as defined by the thermal operating class. The results show the machine learning model can detect three thermal operating classes (i.e., routine, ordinary, or emergency) of the firefighters at any specific location using the sensor temperatures at the ceiling as inputs. This study demonstrates the potential of machine learning models in practical applications to improve firefighters’ situational awareness and enhance their safety.

Keywords: thermal tenability; commercial building; smart firefighting; situational awareness

Introduction

Firefighters work under thermally hazardous conditions. Their various operations expose them to a high risk of casualties. According to an NFPA report [1-2], 65 650 firefighter injuries were reported in 2022 with an increase of 8% from 60 750 injuries reported in 2021. A total of 96 on-duty deaths were reported in 2022, which is the highest number of fatalities since 2013. During fireground operations, firefighters perform strenuous duties while exposed to thermal hazards during firefighting and search and rescue operations. Heat exposure not only presents the risk of burn injuries but also increases the physiological stress of firefighters, which might lead to sudden cardiac death (SCD). In 2022, SCD accounts for the highest portion (about 38 %) of firefighter fatalities [1]. During a fire response, firefighters wear heavy protective equipment which typically weighs more than 30 pounds and perform emergency duties in restrictive spaces under extreme heat. All the hazardous factors are likely to contribute to fatal and near fatal sudden cardiac events [3]. Improvement of the overall safety of firefighters is needed and vital.

Firefighters' tenability is determined by the heat load encountered by the firefighters. Research has been conducted to improve firefighters' tenability by investigating protective clothing [4], protective equipment, and search and rescue tactics [5-8]. This research laid the foundation for tenability limits during the firefighting process. Tests were conducted in full-sized residential structures to measure the thermal burden of firefighters in different job assignments to understand the thermal impact of fire hazards on firefighter's core temperature [9]. Ambient, skin, and core temperatures were measured for different fireground job assignments and firefighting tactics. A series of full-scale experiments were also conducted to investigate the rescue tactics in residential homes considering ventilation and suppression actions and timing [5]–[8]. Thermal exposure to firefighters was quantified with temperature and heat flux. Utech classified firefighters' operational thermal classes into three categories: Routine, Ordinary, and Emergency [10]. Researchers from Underwriters Laboratories modified the tenability limits into five categories: Routine, Ordinary I, Ordinary II, Emergency I, Emergency II, and Emergency III [7]. These criteria can be used to assess the firefighter's tenability, but the previous works were limited to post-analysis of an experiment.

A model that detects the tenability of firefighters in situ in real time and predicts the thermal conditions anywhere in a room based on discrete measurements, however, is lacking. In real fire scenarios, firefighters react to thermal burdens based on their experience and knowledge. Depending solely on experience is not reliable for firefighters on a dynamic fireground, particularly for less experienced firefighters who may lack sufficient practical firefighting experience. With the advancements in sensor technology, continuous collection of data from building sensors is possible. However, when working under emergency conditions, unprocessed information is unhelpful for decision-makers and firefighters. Simple and straightforward actionable information is needed for firefighters to enhance their situational awareness of hazardous environments due to extreme thermal loads. Therefore, developing a model that can detect the firefighters' tenability with straightforward operational classes will inform the firefighters of their thermal exposure and guide their operations and movements.

With the emergence of machine learning (ML) paradigms, ML models have been adopted to predict fire behaviors and structural performance and to inform firefighting operations [11-18]. Combined with real data, state-of-the-art ML algorithms can detect fire development accurately and efficiently, which is beneficial for influencing decisions during firefighting operations. Models that detect firefighters' operational tenability with temperature inputs are complex and depend on fire size, ventilation, and other unknown factors. ML models are designed to find patterns in the data when the relationships between inputs and outputs are complex, as is the case for tenability. Therefore, to derive a relationship between straightforward thermal operating instructions and complex inputs, this research builds upon prior research by developing an ML model to detect firefighter's tenability with time-series temperature. First, the Fire Dynamics Simulator (FDS) is used to generate sufficient synthetic fire data considering various fire sizes and ventilation in a commercial building. The synthetic data is later used to train and test the ML model. Then, a comprehensive parameter analysis is conducted to understand what information is learned by the ML model to make predictions. The proposed model will contribute to our understanding of the thermal exposure of firefighters and enhance situational awareness for firefighters.

Methodology

The objective is to develop and train a new machine learning model capturing spatial- and temporal dependencies in compartment fires to detect the thermal operating classes near-instantaneously at any location in a commercial building during a fire. To this end, the proposed methodology includes: 1) systematically generating synthetic temperature data for various fire conditions, and 2) developing the machine learning model with time-series temperatures to determine firefighter's tenability. These two steps are briefly described hereafter.

Generating data for ML-informed firefighter tenability prediction model

To develop the ML-informed firefighter tenability model with a fast response for firefighting operations, sufficient data that represents realistic fire scenarios is needed. We aim to detect the tenability of firefighters based on sensed temperatures at various locations near the ceiling. Fire behaviors in commercial buildings with different rooms and long corridors are complex, requiring high-fidelity computational fluid dynamics (CFD) models such as FDS for accurate simulation. These models are too computationally expensive to run in real-time, but can be used to generate fire data that are then used to train a surrogate model. We propose to use FDS to model a range of fire cases in a commercial building such as the one shown in Figure 1 (i.e., the layout of a floor from a multi-story commercial building structure). Different fire sizes and ventilation conditions are considered to obtain different fire behaviors as shown in Table 1. The threshold for window breakage under thermal exposure is assumed to be 150 ℃ [11-12]. To generate various temperature conditions, a wide range of fire growth rates are considered as shown in Table 2. Temperatures are collected in 58 different locations at various heights (i.e., 0.6 m, 1.1 m, 1.9 m, and 2.2 m above the floor). The heights are selected by anticipating firefighters' moving paths and the location of the sensors. Nine 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 shown in Figure 1. Grid sensitivity analysis is conducted to ensure the quality of the data. We summarized the output of the FDS simulations to obtain a dataset relating characteristics of fires (fuel, ventilation), inputs (temperature), and outputs (firefighter tenability) for an ML-based tenability model.

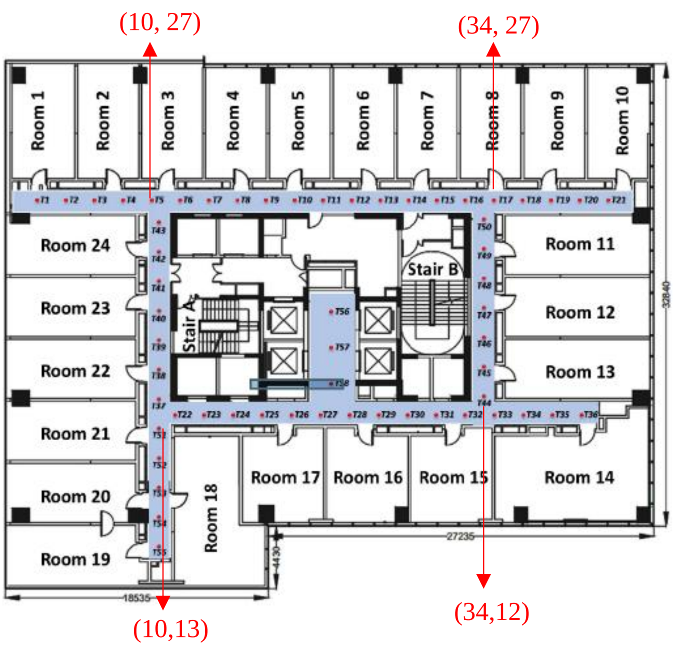

Figure 1. Layout of the commercial building.

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	Fixed value	150 °C [19]

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

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

Developing the ML model

After generating the data, pre-processing such as cleaning the data, and splitting the data, is conducted to obtain the training, validation, and testing datasets for the ML model development. The model inputs include temperature at the height of 3.8 m. The output is the tenability of firefighters in a specific location at different heights. Since firefighters require simple and straightforward actionable information, firefighter tenability is considered a multi-class classification problem with thermal operating classes shown in Table 3. The tenability classes are based on temperature range and are correlated with the duration of firefighters' operation under these conditions. We apply Convolutional Neural Networks (CNN) to develop the model. Performance metrics for classification including accuracy, recall, and precision are used to evaluate the performance. The desired model with the highest performance at a reasonable computation cost is selected.

Table 3. Firefighter's thermal operating classes.

Thermal operating classes	Temperature range (°C)
Routine	[20, 72]
Ordinary I	[72, 200]
Emergency I	[260, 600]
Emergency II	>600

The performance of the developed model in identifying the thermal operating classes is shown in Tables 4-5. Binary classes (Routine and Ordinary) are shown in Locations 1-7 while three classes (Routine, Ordinary I and Emergency I) are observed in locations 8-9. The overall accuracy of Locations 1-7 is above 98%, the recall is more than 85%, and precision is more than 90% except for location 7 which is caused by data imbalance since the least number (only 676) of 'Ordinary' classes is observed. For locations 8-9 with three classes, the model shows a promising accuracy of 98% and 97%. Recall and precision show that the model is good at identifying 3 operating classes with precision higher than 97% and recall higher than 96% except for the class ‘Emergency I’ at location 9. This is also caused by data imbalance since location 9 only observes 1372 labels of ‘Emergency I’ while location 8 observes 10934 labels of ‘Emergency I’.

Table 4. Performance of the locations 1-7.

Location	Accuracy	Recall	Precision
1	98.8%	86.3%	92.9%
2	99.3%	90.0%	91.8%
3	99.2%	96.7%	99.1%
4	99.2%	92.5%	90.8%
5	98.4%	92.2%	95.8%
6	99.2%	97.5%	99.0%
7	99.5%	84.9%	79.7%

Table 5. Performance of locations 8-9.

Location	Class	Recall	Precision	Accuracy
Location 8	Routine	98.90%	98.20%	97.90%
	Ordinary I	98.40%	97.00%	
	Emergency I	95.50%	99.30%	
Location 9	Routine	99.70%	97.20%	96.90%
	Ordinary I	97.50%	96.60%	
	Emergency I	42.30%	99.30%	

Concluding remarks

A surrogate model (trained on high-fidelity FDS simulations) that provides detections of firefighter’s thermal tenability with well-characterized uncertainty in commercial buildings during fire events is developed. The model can be extended to detect the tenability of firefighters under thermal exposures at any location which can significantly improve firefighters’ situational awareness. This information can easily be used to determine optimal search and rescue paths.

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