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Machine Learning Driven Smart Fire Safety Design of False Ceiling and Emergency Response

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Abstract

In modern buildings, false ceilings are widely used for building services systems and aesthetic purposes, but they also pose challenges in terms of fire safety. A fire accident typically results from the failure of multiple safety measures or components. In many fire accidents, fire and smoke reached the false ceiling and kept spreading in the interstitial space without any detection. This study first generates a numerical database of false ceiling fire scenarios by varying the room dimensions, false-ceiling leakage area, fire size and locations. Then, a smart model based on machine learning to predict the fire smoke motion below and above the false ceiling is developed. The trained model is capable to predict the activation time of fire detectors and sprinklers for any given false ceiling design and fire scenario. This methodology enables a designer to generate multiple fire scenarios and determine the available safe egress time (ASET) for performance-based fire engineering designs especially in terms of fire detection time. In case of a real fire, with the data feed from the fire sensor network, the trained machine learning model can further predict the critical building fire events with the false ceiling, such as multi-compartment fires, smoke in the evacuation path, and structural failures. This work proposes a smart framework for improving the building fire safety design of false ceilings and the sensor-driven fire forecast to support firefighting.It enhances the emergency response processes by enabling dynamic risk assessment through prediction of critical events.

Keywords: *building safety; artificial intelligence; fire detection; data-driven forecast; smart firefighting*

1. Introduction

In modern buildings, false ceilings are fairly common. Typically the building services systems, such as mechanical and electrical equipment, ductwork, piping, and conduit, run over the false ceiling. As shown in Fig. 1, false ceilings, sometimes called "suspended ceilings" or "dropped ceilings", can also be used for aesthetic purposes. It is usually constructed of gypsum board, PVC panels, tiles, etc. Generally, the false ceiling is kept at a certain distance from the main ceiling with the use of metal wires. The interstitial space between the false ceiling and the main ceiling can be as huge as 0.5m to 1.5m.

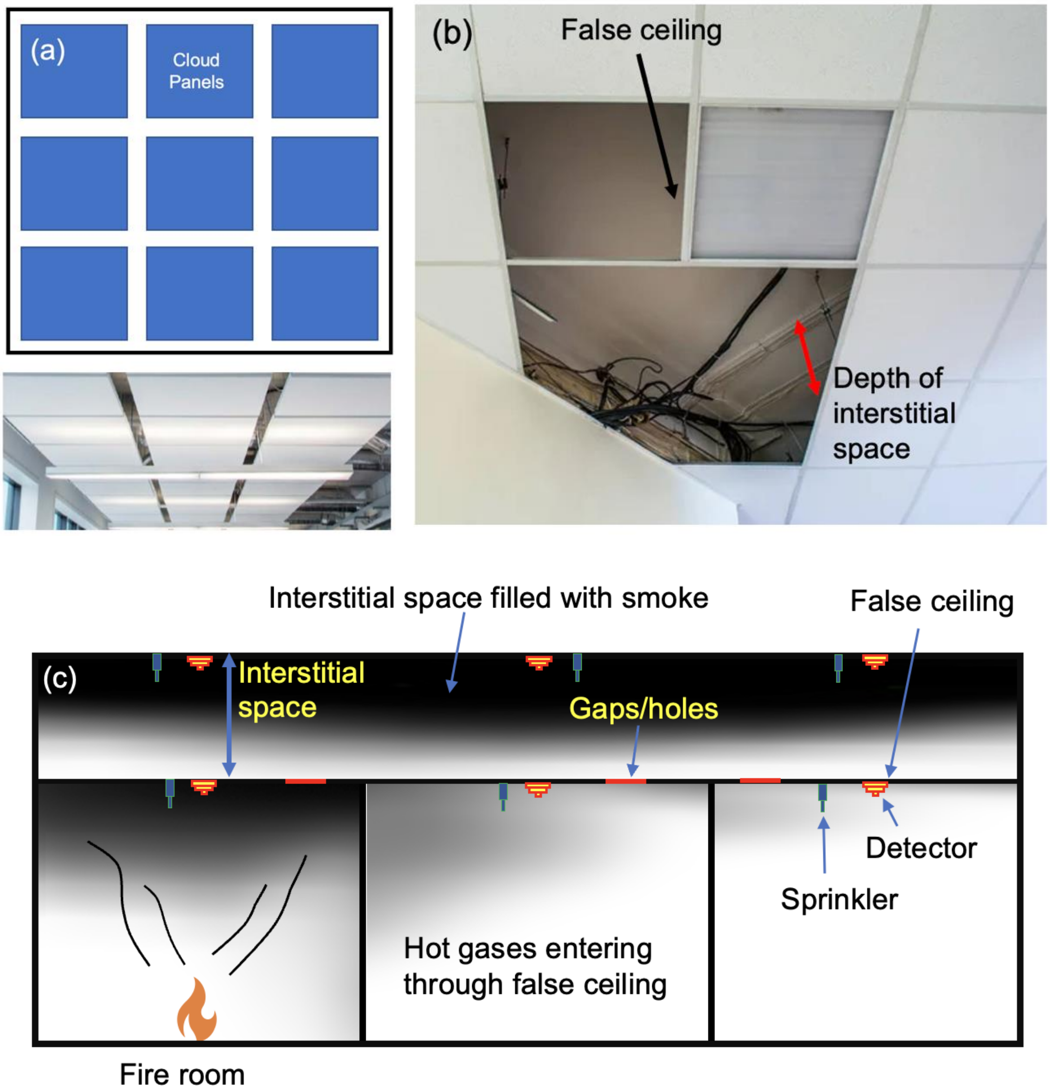

Fig. 1. (a) typical false ceiling design, (b) false ceiling with partial panels removed, and (c) movement of the smoke through the false ceiling through holes.

The interstitial space between the false ceiling and the main ceiling may contain a significant amount of combustible [1,2]. In general, cables, conduits and ducts run through the interstitial space all over the floor. It is, therefore, common for interstitial space to be open, and there is no compartmentation to occur between adjacent compartments. Some of the reasons for keeping it open and providing no separation include complex design increases in maintenance issues and the cost of sealing cable trenches and providing fire-resistive sealants for piping and supports. Furthermore, the separation also increases construction and material costs. The open interstitial space (no partition) may have an adverse effect in terms of fire and life safety, as it increases the risk of de-compartmentation. The false ceiling provides a pathway for smoke and flame to travel to locations remote from the original fire source in Fig. 1.

Once the smoke or fire reached the interstitial space through upward motion, the fire would travel horizontally in the open space above the false ceiling, and then downward flow into adjacent compartments. Such fire spread was observed in a fire accident that occurred in the Plasco Building in Tehran (2017), where the fire reached other compartments through false ceilings [3]. Furthermore, through the leakages in the compartment, the fire can reach above the false ceiling as observed in some experimental studies and fire accidents [2,4–6]. Typically, leakage is always present in a compartment; sometimes due to construction gaps that are left unfilled, sometimes a few PVC or gypsum panels of the false ceiling are removed or damaged. Furthermore, the smoke may reach other areas and, more importantly, in corridors that can impede the evacuation process of the occupants and the ingress of firefighters. Despite the prevalence of false ceilings in residential and industrial buildings, very limited study has been performed in terms of their detrimental effects on fire and smoke spread inside the building during a fire accident [7,8]. The challenges associated with false ceilings are crucial issues among the fire protection community regarding the potential danger resulting from smoke and fire leakage [2,9,10].

While looking for the fire, the firefighters may need to open the attic or false ceiling and put off the fire in the concealed spaces, which is a challenging task. The sudden opening of the false ceiling (or attic) allows fresh air to come in. The quick contact between fresh air and high-temperature fuel may cause an earlier flashover, a smoke explosion or backdraft, which are too fast to be suppressed [10–12]. Delays in identifying the location of the fire and challenges in suppressing it from the false ceiling can cause the fire to keep heating the structural components, which may lead to their collapse. The collapse of slabs and a false ceiling were the cause of many fatalities among firefighters [13–15]. In a college in Auckland (New Zealand, 2007), a fire was initiated in the false ceiling. Even for more than 40 firefighters, it was a challenging task to put off the fire, as the fire reached two classrooms when they removed the false ceilings [16]. The smoke was observed in other parts of the college as well. In a fire accident in the US (1998), when firefighters pulled ceiling tiles to suppress the fire in the false ceiling, the fire compartment experienced a flashover that led to the death of two firefighters [17].

Due to the presence of combustibles, fire can be ignited above the false ceilings and reach the compartments. The '*infamous*' fire accident of Stardust Nightclub in Ireland in 1981, where around 48 people died, is also a case of spreading of fire from a false ceiling to the floor area. The fire in Norte-Dame Cathedral in Paris (France, 2019), was initiated in the attic region and spread other parts of the structure [18]. In 2010, while responding to a fire in a church, a firefighter died when the structure collapsed due to intense burning above the false ceiling. The report showed that the structure was mostly clean of fire until firefighters reached the attic, where they found a considerable amount of fire which was difficult to control [17].

During a firefighting operation, it is critical to know the exact location of the fire. The fire may be concealed above the false ceiling, making it challenging for firefighters to find. Even when a design of the building is complying to the latest standards, it is not uncommon for the fire or smoke to spread other parts of the building particularly through false ceilings, as a result of containment failures during a fire. These undetected fires (or delay in detection) above the false ceiling can act as a pre-cursor event for future critical events such as multi-compartment fires, failure of structural and non-structural components, and so on [13]. Modern buildings may be equipped with intelligent fire alarm control panels. With fire and smoke detectors, the panel can indicate the exact room location of the fire [19,20], which is a prototype of Internet-of-Things (IoT) sensor network. If the detectors are installed in the building, the location of the fire room can be obtained from the fire panel. These panels or screens (annunciator or mimic panels) are generally installed at the entrance of the building, which helps the firefighters to determine the location of the fire. It is worth noting that detectors and sprinklers are often not installed above false ceilings or cloud ceilings [1,20], despite the risk of smoke entering to the false ceiling and igniting the combustibles inside.

Recently, Artificial Intelligence (AI) methods, especially the Machine Learning (ML) models, are introduced into fire research at different stages [21], including fire safety design [22], fire identification [23,24], evacuation [25], and fire forecast [26][12]. For example, AI model can predict the smoke motion inside the atrium to conduct fire safety performance-based design (PBD) that can improve the design and review efficiency [21,27]. In the PBD approach, it is required to create various fire scenarios to evaluate the Available Safe Egress Time (ASET) which is set based on the worst-case fire scenario. An AI based model allows to create various fire scenarios. Based on the compartment geometry and other parameters, a designer can know the detection time, visibility, concentration of CO or other poisonous gases in the room, false ceilings, remote regions, or corridors. Prototypes of smart fire digital twins equipped with AI cores and IoT sensors for buildings and tunnels are also demonstrated in previous studies [28,29]. Compared to the temperature and smoke concentration information in a real fire scenario, the internal and external flame and smoke images are easily accessible. Thus, computer vision methods also show great potential to be applied in smart firefighting to identify the fire size and forecast the fire development [30]. Meanwhile, AI/ML models are also proven to be able to predict critical events, such as flashover in a compartment fire [31,32]. However, it is worth noting that the those-above mentioned models are only validated in relatively simple scenarios, the interactions between fire and building components, e.g., the false ceiling, are not considered so far.

This paper proposed a methodology to develop a database based on computer simulations and develop an AI model which can assist the future designs to generate critical fire scenarios. The model is capable of predicting the activation time of fire detectors in the false ceiling based on the compartment characteristics such as area and height of the room and so on. With the IoT sensor network, the model can also be used in future smart firefighting practices to forecast critical events in real-time.

2. Fire hazards and scenarios with false Ceilings

2.1. Past experiments

Despite of critical nature of such incidents and the complexities involved in firefighting operations while dealing with the space above the false ceiling, limited attention has been given, especially in the research point of view. An important study regarding the smoke movement in the false floor through the suspended ceiling was conducted by the US Department of Commerce in 1982 [4]. In the test, smoke concentration in compartments with false ceilings was investigated. In the tests, a typical case of a hospital facility was chosen, including four rooms, a corridor and an open unseparated interstitial ceiling region), as shown in Fig. 2.

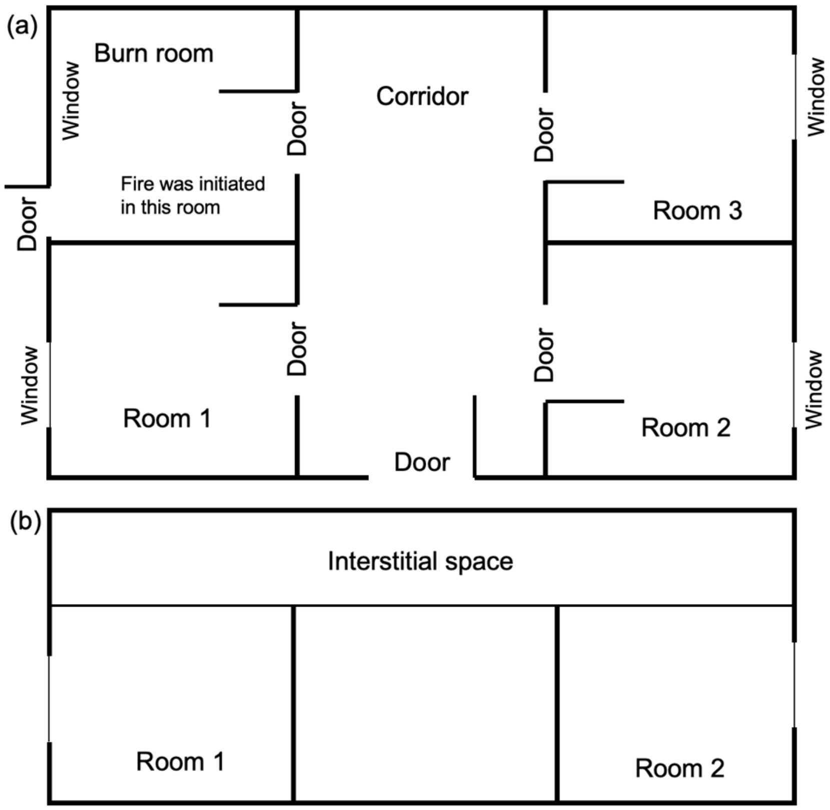

Fig. 2 Experimental study conducted by [4] (a) Plan view (b) sectional view

In these tests, the extent of smoke penetration through the ceiling was evaluated for different intensities of fire, from smouldering fires to high-energy flaming fires. Smoke concentrations were determined by measuring smoke obscuration and CO concentration using smoke meters and CO probes, respectively. The effects of the ventilation, occupancy space exhaust and interstitial space smoke exhaust on smoke concentration in the test facility were also investigated. In addition, a hazard analysis, limited to smoke obscuration and CO concentration, is included. Activation of detectors and sprinklers was recorded. Smoke was measured in the rooms and corridors. Jin [33,34] recommended a critical level of obscuration based on "*not reducing*" the walking speed below the blindfolded subject in a smoke-free environment. The prescribed valve of smoke obscuration was 0.25 OD/m (Obscuration density per meter) [4,33,34]. A total of twelve tests were performed for various fire intensities and ventilation conditions, such as the door of ignition room closed and open, and the exhaust open and close. In the low-energy tests, mattresses with fire retardant material were used, on the other hand, for high-energy tests, mattresses were filled with polyurethane foam. In all tests, the fire was able to reach adjacent compartments.

The Fire Protection Research Foundation conducted a study to determine the requirement for sprinklers above cloud ceilings [35,36]. Cloud ceilings refer to the ceiling having ceiling panels sitting beneath the main ceiling of the structure (Fig. 1a). Various tests and computer simulations were conducted to test the activation of sprinklers when cloud ceilings are present. The effect of the cloud ceiling width, area, gap between panels, and ceiling height was considered in the study. Based on this study, in 2016 Edition of NFPA 13 permits the omission of sprinklers above the cloud ceiling if the opening area is below 20% of the total ceiling [1]. Although efforts to improve the computational modelling and use of mathematical modelling in fire sprinklers have been carried out for more than three decades [37–39], it is worth noting that this study is one of the few instances where validated computational results by the Fire Dynamics Simulator (FDS) can be accepted in a standard.

2.2. Fire and life safety practices

In the past century, many methods have been introduced for life and property safety in a fire accident. Without a doubt, automatic sprinklers are proven to be the biggest "*life saver*" in a fire. Due to modern construction methods and the introduction of innovative materials, various types of sprinklers are regularly introduced in the industry [1]. The sprinklers activate at a certain "design temperature". Therefore, the fire should be large enough to generate enough heat to make the bulb burst. It is required to have more sensitive devices that can detect fire in its early stages. Smoke and heat detectors are more sensitive than automatic sprinklers [20].

The characteristic time of the fire growth is quite low, and the fire can spread significantly fast [40]. When the firefighters arrive at the scene, the fire may reach a critical stage. So, early detection is vital for effective firefighting, not only for occupant safety however the safety of firefighters. Along with early detection, determining the fire location is critical information, especially for firefighters. Generally, in modern buildings, detectors are connected to the building fire alarm control panel that can tell the exact room of the fire [19,20].

The fire or smoke can reach a false ceiling and eventually other parts of the building. The time of fire detection in the false ceiling would typically depend on the opening area in the suspended ceiling, fire location and fire size. It is also not uncommon that no fire detectors are installed in the above ceiling, and the fire remains undetected. Knowing the information about the presence of the fire above the false ceilings can help the firefighters to suppress the fire. This paper developed an AI model to predict fire detection time in the compartment and above the false ceiling. The model can predict the time of fire reaching the false ceiling. The database is generated using FDS (a CFD tool for fire-related problems) to predict the time of activation of the detectors and sprinklers in a compartment [41,42]. Thus, how the CFD fire simulation evaluates the time of activation of these fire service devices is critical that should be clarified first.

Fire detection time of smoke detector. Smoke detectors are the most commonly used devices for fire detection [20]. Due to high sensitivity, smoke detectors are capable of detecting fire in the very early stages of fire. The major parts of smoke detection are the smoke chamber, where smoke is accumulated, and obscuration is measured. A threshold value of obscuration is provided to activate the smoke alarm. The time of detection can be evaluated using the FDS [41,42]. To determine the smoke obscuration, in the current version of FDS, two different models are employed; one is proposed by Heskestad [43,44] and another by Cleary et al. [45]. In the Heskestad model [46], FDS evaluates the mass fraction of smoke in the smoking chamber. Clearly et al. [45] method argues that before the smoke reaches the smoke chamber it passes through the housing of the detector. Therefore, their correlation includes the *time lag* associated with the smoke entering the chamber and housing.

Response time of Automatic sprinklers. Different types of automatic sprinklers are available which are basically categorised on the basis of temperature, occupancies and so on [47]. The sensitivity of a sprinkler is generally measured by Response Time Index (RTI) [41]. Temperature reaching the bulb is evaluated by considering the heat transferred to the bulb by convection and conduction. The RTI can be evaluated by utilising the time constant. Heskestad and Smith [48,49] developed a plunge test to determine time constant. The RTI for a sprinkler is generally provided by the manufacturer and typically set for particular type of sprinklers such as $80s^{1/2}m^{1/2}$ or more for standard sprinklers and $50s^{1/2}m^{1/2}$ or less for fast response sprinklers.

Testing of false-ceiling systems. Various lab tests for the ceiling material are conducted to ensure that the fire would not spread from suspended ceiling system, such as BS 476, EN 1365-2, ASTM E119. Therefore, to limit the fire or smoke spread the compartment it is required to have proper sealing material (fire rated), regular inspection, and proper maintenance. However, it is not uncommon that smoke or fire was observed in adjacent compartment or in the escape routes of the occupants during a fire accident. Even a slight gap in the ceiling can create a path for smoke or flames to escape the compartment where the fire originated.

Key consideration in fire safety designs. In PBD approch it is required to present various fire scenarios to demostrate that fire safety goals are achived. Life safety is generally the minimum requirement in fire safety codes, which requires that the occupants should be able to evacuate the buildings before conditions become untenable. For this purpose, the key parameters a designer needs to look into are: concentration of poisonous gases (CO, HCN, or other poisonous gases), thermal effects, and visibility. According to the various building codes [46,50–52], the Fractional Effective Dose (FED) of CO and thermal effects must be lower than some critical values (e.g., 0.3 [51,52]).

The designer must calculate the ASET to demonstrate that the occupants have sufficient time to evacuate the building (before FED or visibility reached design limit). ASET must be higher than the Required Safe Egress Time (RSET). The designers are interested in reducing the RSET, so that they can achieve the design objectives for lower value of ASET. It must be noted, the designer needs to include the fire scenarios that include the corridors, adjacent compartments, stairs to ensure the safe evacuation of the occupants. The visibility criterion is applied to the corridors and the regions beyond the room of fire origin.

2.3. Numerical model for building fires with false-ceiling

Spot-type detectors such as smoke detectors, are generally more sensitive and act faster than sprinklers due to activation mechanisms. It is possible that fire or smoke reached the false ceiling, but it will be not detected until a sufficient amount of smoke filling in the false ceiling region. The time of activation of detectors will largely depends on many factors as discussed above. However, the area of the leakage plays a critical role in fire detection. In the experimental study [4], it was observed that the fire could reach above the false ceiling even leakage area is very small [2,3,53].

The fire detection may be delayed due to many reasons, such as low smoke production, large compartment size, the initial location of fire being far from the detectors, and a smaller leakage area. In the current study, an AI based model is generated to determine the effect of these parameters on the timing of detection. The machine-learning model presented in this study provides a methodology for forecasting time of detection that can be used for fire safety designs and smart firefighting.

Some of the key perimeters that affect the activation time of the detectors and sprinklers are selected in this study. The fire size is one of the key parameters that dictate the time of the activation of the detector. During the initial stages of the fire, the fire size may not be very large, but there might be sufficient smoke to activate detectors. Four values of heat release rate (HRR), in the range of 20 to 80 kW/m^2, are chosen. The burner (fire) size of 1 m^2 is used for all cases.

As the room size increases, the smoke would make more time to generate the ceiling jet or accumulate at the ceiling level or reach all detectors. Three different sizes of compartments are used in this study to demonstrate the effect of compartment size and generate the database for AI model (Table 1). The spread of fire in a compartment also depends on the fire location. During the initial stage of the fire, the smoke would spread evenly throughout the compartment. However, if the fire is initiated at other places, such as in a corner, then the smoke may need to travel a longer distance to activate the farthest detectors. For generating the AI database, two fire locations, the centre and corner of the compartment, are used.

The travelling time of the smoke reaching the ceiling depends on the height of the compartment. In general, the detection time would be lower for a compartment of lower height. Compartments of three different heights are used. It is worth noting that the height of interstitial space above the false ceiling region is fixed to 1 m for each case.

The amount and timing of smoke reaching inside the interstitial space above the false ceiling depends on the leakage area. To determine the effect of leakage area on the smoke detection time, three different values of the leakage are selected. It is worth noting that, generally, the leakage area would be due to gaps at different places or breaking/cracks in the intermittent ceiling, however for the simplicity of the numerical simulation, a single leakage hole of various sizes (Table 1) is used in the current study. When studying realistic fire conditions, more sophisticated fire simulation methods for very small holes at various locations (available in FDS) can be used. For a base case for each scenario, detection time for no leakage is used in the present study.

Table 1. Perimeters considered in generating AI Model

Parameter	Range	Number
HRR (W/m^2)	20, 40, 60, 80	4
Room Size (m^2)	9, 25, 64	3
Fire location	Corner, centre	2
Ceiling height (m)	4, 5, 6	3
Leakage area (m^2)	0,0.16,0.25,0.36	4
Total		288

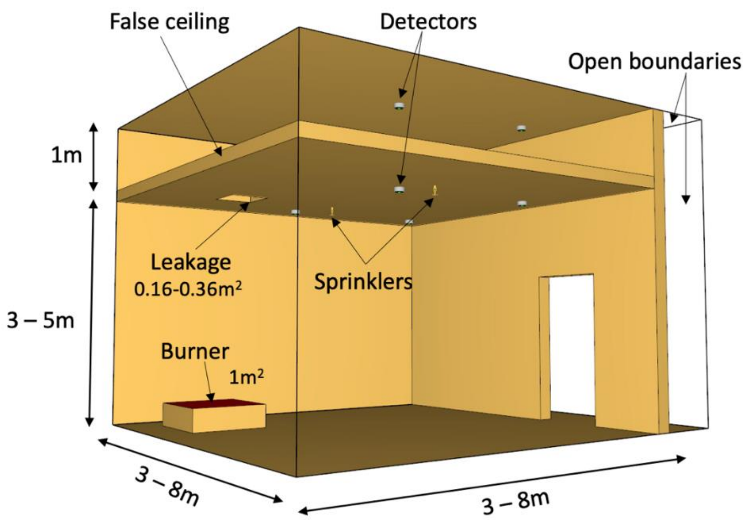

Fig. 3. Numerical model for false ceiling fires

Over the past few decades, the capabilities of CFD fire modelling have been used extensively for fire engineering design and fire safety research. The FDS (developed by NIST) is the most widely used CFD modelling software for fire simulations. In FDS Large Eddy Simulation (LES) turbulent model is implemented to solve the airflow and smoke transport in the fire. In the LES model, energy and momentum of the large eddies are resolved while the eddies smaller than the mesh size are modelled.

Therefore, grid independency test is not required in LES, while the sensitivity of the analyses to the mesh size needs to be evaluated. To examine mesh sensitivity and determine the optimal mesh size for CFD simulations in this study, various mesh sizes were tested. Based on detection time, a mesh size of 0.1m was found to provide the reasonable results, with no further improvements observed when using finer meshes **Fig.** 3 shows a computational model used in the study. To generate the database for developing an AI model, a total of 288 cases are simulated in FDS, as shown in Table 1. It is worth noting that for all cases, the same ventilation condition (a door of size of 1×2 m^2) is used.

2.4. Numerical fire database

Eight smoke detectors are installed in all cases (four in the room and four above the false ceiling). The average time of activation of four detectors in the room and false ceilings is recorded for developing the AI model to learn from the data. Although in many cases, the outcome is intuitive, such as a reduction of the activation time with the increase of fire size, in some cases, the results can be counter-intuitive or unpredictable due to the complexity of various parameters. In some cases, it was observed that due to higher leakage area, the detection time in the compartment increased and the time of fire detection in the false ceiling reduced (large openings).

Knowing the exact time of the fire allows determining the chain of events that may occur inside the building which provides time to firefighters for assessing the situation. In the current study, although smoke detection is the major concern (predict and help firefighters), however sprinkler activation in the room is also measured. If the sprinkler operates, in most of the cases (especially for small fires), the fire can be suppressed [54]. In the current study, two sprinkler links are installed inside the compartment to predict the time of their activation. Standard sprinkler with activation temperature of 68℃ with an RTI of $100s^{1/2}m^{1/2}$ is used. In most of the occupancies, generally, standard response sprinklers (RTI of 80 or above) with temperature rating of 68℃ are utilised [1].

The average time of their activation time is considered to generate the database. In summary, the samples in the database are summarized with the input tensor: [HRR, Room size, Fire Location, Ceiling height, Leakage area], and paired with the output tensor: [$T_{r,d}$, $T_{fc,d}$, $T_{r,s}$, $T_{fc,s}$], where the subscript r, fc, d, and s represent room, false ceiling, smoke detector, and sprinkler, respectively. It is worth noting that some of other critical perimeters that are critical for the tenability condition of the rooms and corridors and for fire emergency responses such as soot concentration, CO concentration, and other species can also be calculated from the FDS. Determination of these perimeters requires inputs from experimental data. An extension of this study aims to predict these parameters and examine how fire can propagate from the false ceiling to the escape route (or egress path) and the ingress path for firefighters. The focus of this study is solely on predicting the detection time and demonstrating that fire (or smoke) can reach false ceiling and adjacent compartments and how it can be incorporated with the smart fighting system.

3. Dynamics of False Ceiling Fire

This section discusses the movement of smoke (hot gases) to the false ceiling through the leakages, as observed in the numerical simulations. Table 2 and Figs. 4 & 5 present four cases to discuss the smoke dynamics of fire in false ceiling. The smoke concentration is presented in the form of visibility. Fig. 4 and Fig. 5 show the temperature and visibility profile of the fire compartment and false ceiling after three minutes since ignition, respectively. The first few minutes are critical in terms of the occupant's safety, while the later stages affect the ingress and egress of the firefighters. It is clear from Fig. 5 that the false ceiling is filled with smoke, where the temperatures do not increase drastically and may not be high enough to ignite any combustibles in the early stages of the fire (Fig. 4). Nevertheless, it is worth noting that a very low HRR (80 kW/m^2) is taken, in the case of real fires, it may be much larger, which can ignite the combustibles present in the false ceiling, as observed in the case of the Plasco building fire accident [3]. In all cases, the hole location (leakage) is near the corner to understand the effect of the fire location. The hole location would also affect the start of rising in temperature and soot concentration above the false ceiling. As the hole is farther when fire is located at the centre, a slow rise in temperature is observed in the early stages of the fire (Fig. 4).

Table 2 Cases to present the smoke dynamics in the false ceiling

Case	Room Area (m^2)	Height (m)	Fire Location	Hole Size (m^2)	HRR (kW/m^2)	False Ceiling condition after 3 mins	
						Temperature	Visibility < 5m
a	25	4	Corner	0.36	80	32-42	Yes
b	25	6	Corner	0.36	80	32-40	Yes
c	25	4	Centre	0.36	80	32-38	Yes
d	25	6	Centre	0.36	80	32-38	Yes

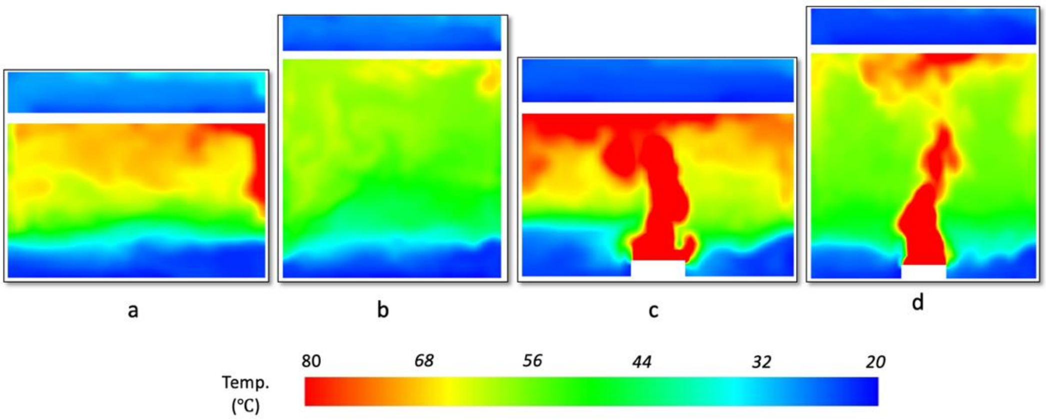

Fig. 4 Temperature profiles after three minutes at the centre of the compartment

Visibility is one of the key parameters in fire safety designs, as mentioned in Section 2.2. Fig. 5 shows how the visibility decreases at various time intervals (1, 2, and 3 minutes since ignition). All cases clearly show that the visibility in the false ceiling is decreased below 5 m (Fig. 5). Case 'd' shows the effect of height on the smoke concertation in the false ceiling. Due to the larger height of the compartment, the rate of rise in the smoke concentration is lower.

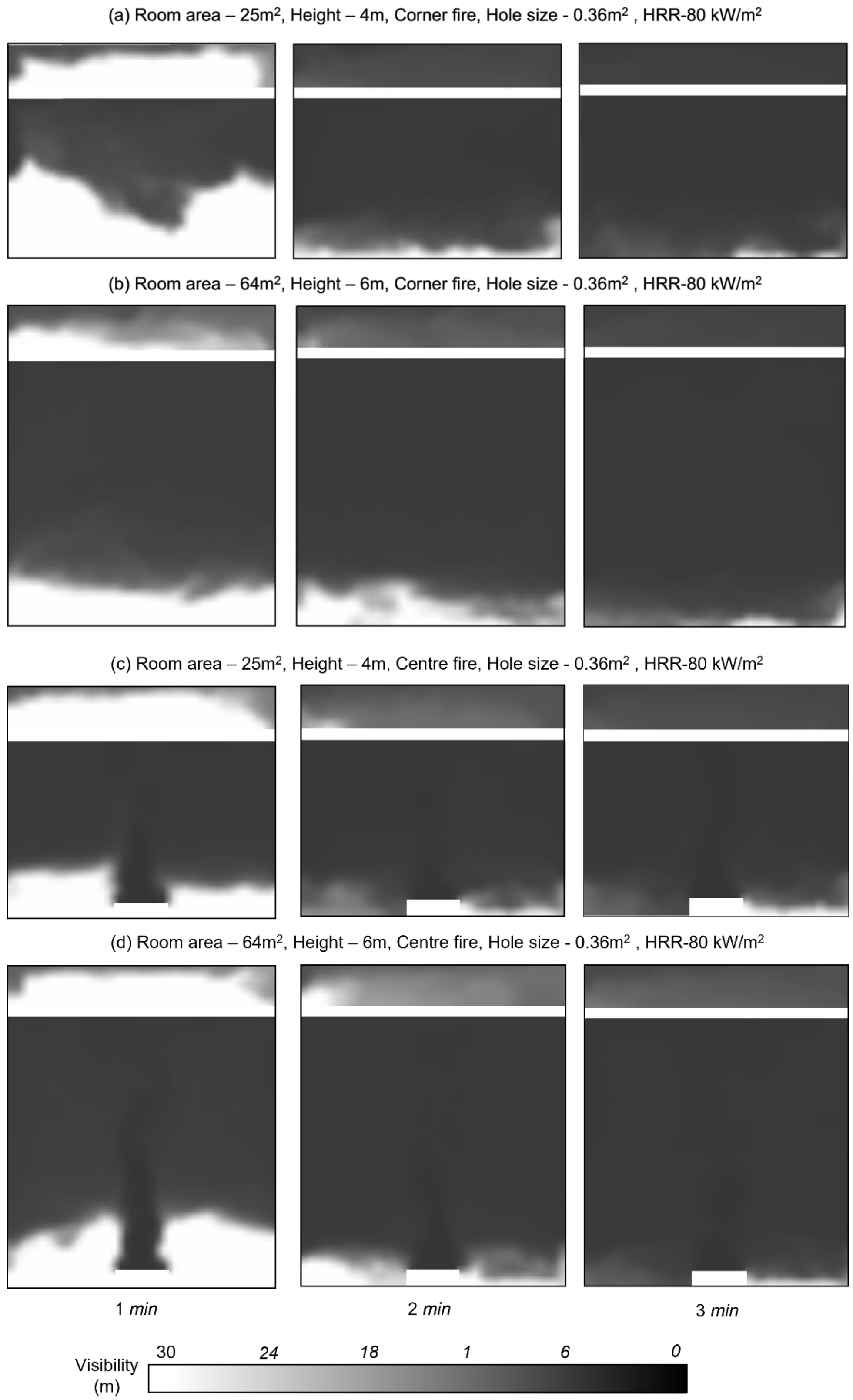

Fig. 5 Visibility profiles at the centre of the compartment at various time intervals.

The smoke can easily enter from the false ceiling to corridors and adjacent compartments. To demonstrate the movement of the smoke to the adjacent compartment (corridors) through the leakage in false ceiling, a case is numerically investigated, as shown in Fig. 6. A fire size of heat release per unit area of 250 kW/m^2 is taken to present the realistic fire scenario. After 5 mins of the fire, the false ceiling was filled with smoke and enter in the adjacent compartment (Fig. 6a). Visibility also reached below 1m in fire room and false ceiling, furthermore the visibility starts decreasing in the adjacent compartment (Fig. 6b and 6c). The smoke layer can reach below 2m above the floor level, which is considered critical in terms of the evacuation [51,52]. Another critical effect on human safety is the higher concentration of poisonous gases, such as CO and HCN, which can also enter the corridors or other regions of the building through false ceilings. To simply the analysis, the fire hazard of poisonous gases is not discussed in the current study.

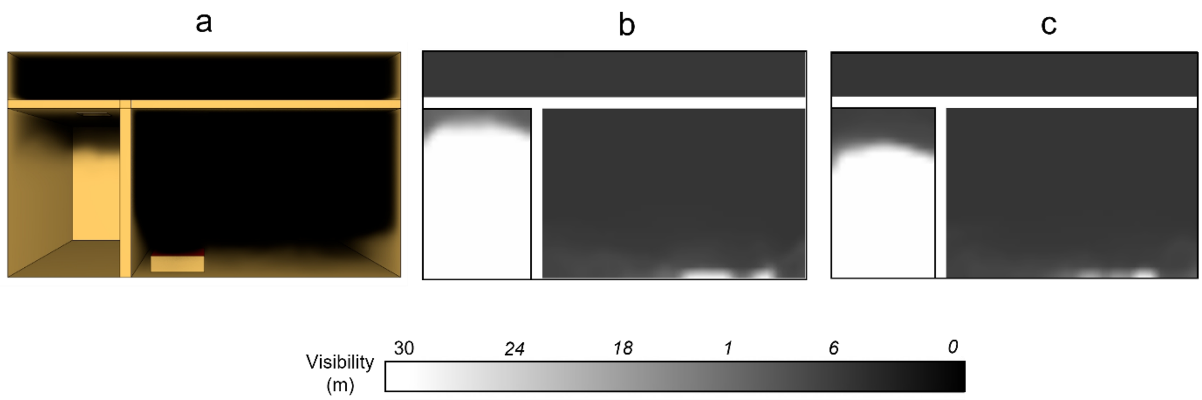

Fig. 6 (a) Smoke in the adjacent room at five minutes, and Visibility profile at (b) 5min & (c) 8 mins

4. Machine learning method

The terminology of Artificial Intelligence (AI) was firstly proposed at the first Dartmouth Conference on Artificial Intelligence in 1956 [55]. After several decades of development, AI technologies are becoming mature and have been widely applied in our daily life, e.g., face recognition, preference recommendation, Natural Language Processing (NLP), speech recognition, etc.

In the training process, the neural network (NN)-based AI model update the parameters (weights and biases) in each neural unit to match the label and reduce the loss function. The knowledge (or the characteristics) of the database is then stored in the parameters of each layer after training. Different from the traditional data-driven method using optimization algorithms [56], the NN-based AI model has a stronger characteristics extraction capability, which imitates the human brain and learns hidden features from the big dataset [29]. Moreover, the AI model can achieve super-fast response with a large complexity at the second level, whereas traditional optimization algorithms typically increase the computational speed with simplifications that scarify the model performance and accuracy. In this work, a synthetic database of room fire cases with and without false ceiling is established to train the AI model.

The effect of the false ceiling on the smoke detection time both in the room and above the suspended ceiling is presented.

4.1. Back Propagation (BP) Algorithm

BP algorithm is one of the most widely used neural network-based AI models. The principle of BP algorithm is to adopt the steepest gradient descent path in the error back propagation process to regulate the weight and threshold value in each unit to minimize the loss function. The training procedure of BP neural network can be divided into two stages, as shown in Fig. 7._The first one is the *forward propagation of input data*. During this stage, the weight and threshold value of neural units are maintained constant. The signal propagation is one-directional (the current layer's status only affects neurons at the next layer). Typically, the output of the neural network cannot match perfectly with the label, then it switches into next step *(back propagation of error signal)*. At this stage, the error signal (loss function), i.e., difference between the real output and expected output, is propagated from the output layer to the input layer in a layer-by-layer manner. During the back propagation, the parameter in each layer is updated by gradient descent method, as shown in Eq. (1).

$$x_{k+1} = x_k - \eta_k g_k \tag{1}$$

where x_k is the parameter matrix of the current neural network in step k, and x_{k+1} is the updated parameter matrix in step k+1; η_k is the step length in the gradient descent process, also known as learning rate in machine learning; and g_k is the gradient of the current loss function.

By reducing the loss function, the outputs of the AI model get closer to the expected ones. When the loss function approaches its minimum point, i.e., the value does not change with iteration epochs, the model is regarded to be convergent. The parameter in each unit (the weight and threshold values) at the minimum point is a group of solutions for the well-trained AI model.

4.2. Description of Artificial Neural Network (ANN) model

This study aims at predicting the smoke detection and sprinkler activation time considering the effects of false ceiling with different conditions, which is a typical regression problem with multiple inputs (fire scenario parameters) and single output (detection time). Therefore, the Artificial Neural Network (ANN), widely used in static predictions, is adopted to facilitate the critical time. The ANN model is built with TensorFlow Core v2.2.0.

The structure of ANN model is demonstrated in Fig. 7. As shown, the proposed model consists of an input layer, three hidden layers with 24, 128, 64 units, respectively and an output layer. The proposed ANN model has five input parameters, i.e., HRR, room size, fire location, ceiling height, and leakage area, and four output parameters, i.e., the smoke detector activation times with/without false ceiling, and the sprinkler activation times with/without false ceiling. The selection of input and output parameters are discussed in detail in Section 5. To avoid overfitting, an initial dropout rate of 0.1 was set for each Fully-Connected (FC) layer. Rectified linear units (ReLU) activation function was added for all hidden layers.

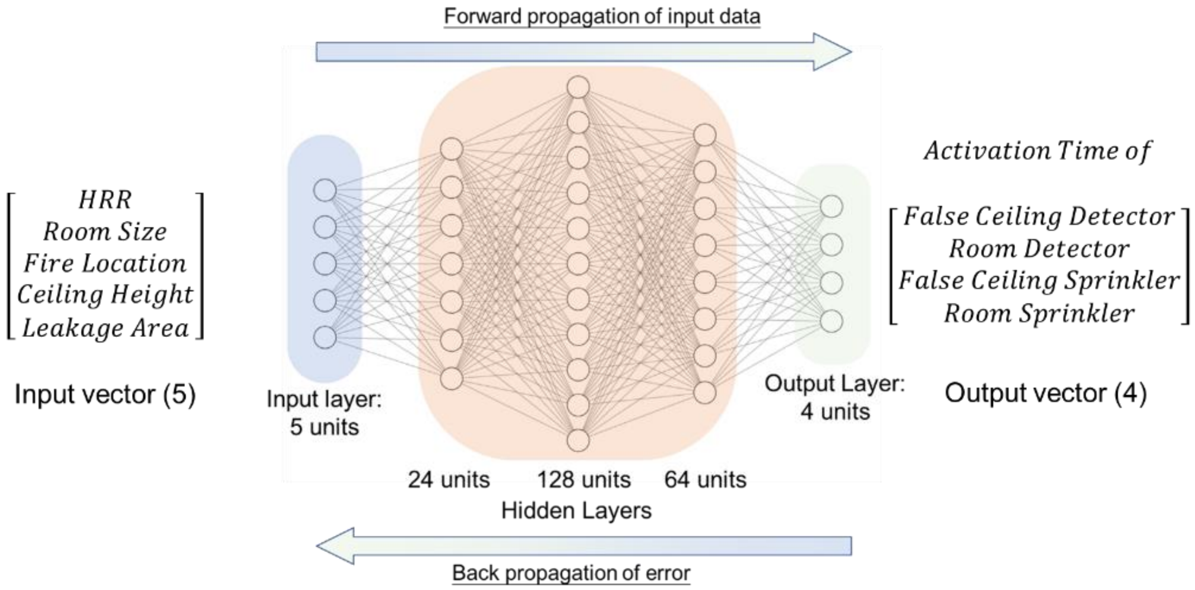

Fig. 7. Diagram of Artificial Neural Network (ANN) model

4.3. Training of AI model

In this study, mean squared error (MSE) and coefficient of determination (R^2) are adopted as the loss function and metrics for their appreciable performance on the regression problems. According to preliminary trials, the initial learning rate and training epochs were set as 0.001 and 500, respectively. The batch size is set at 16 to balance the generalization and model convergence speed. The ANN model extracted the knowledge of the critical times with the input parameters at each epoch. The correlation was stored into the parameters of each neural unit of the network and can be applied to predict the critical fire event for unknown compartment fires.

The database established in Section. 2 is divided into training, validation, and test set with the ratios of 60%, 20%, and 20% respectively. The database is first separated to training/validation subset and testing subset with the ratio of 0.8 and 0.2. For the test sub-set, 56 samples are selected based on two principles. First, the test sub-set can cover all the simulated parameter range. Second, the test sub-set contains at least one group of samples with four parameters the same while traversing the last parameter. For example, four samples with 0, 0.16, 0.25, 0.36 m^2 leakage area and the same HRR, Room size, Fire location, Ceiling height are included. The principles ensure the testing subset has a wild range and help assess the model generalization capability effectively. The training/validation subset are then separated by 0.6/0.2 ratio randomly to avoid potential imbalance data distribution.

The model performance on the training and validation set during the training is presented in Fig. 8. As shown, the training efficiency is high at the first 100 epochs, while the performance improvement slows down after 200 epochs (the number of iteration). The R^2 (Coefficient of Determination) value keeps increasing until 450 epochs or so, as well as the MSE value decreases, indicating that the selected epoch number of 500 is a sufficient choice. Finally, the R^2 value converges to around 0.96, indicating that the ANN model has already well studied the correlation between the fire scenario conditions and the critical time, and the MSE converges to less than 0.01, so the overall error is lower than ±10%.

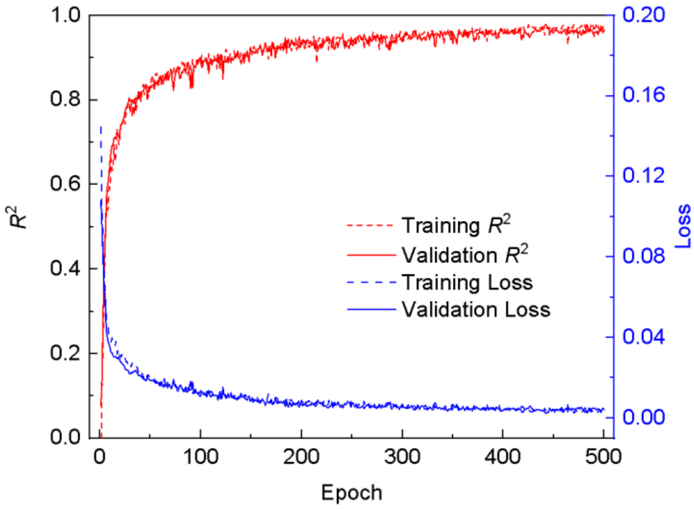

Fig. 8. Model performance during the training process

It should be noted that prior physical knowledge can be introduced to help train the ANN model. For instance, the smoke detector and sprinkler above the false ceiling cannot be activated when the leakage area equals zero because there is no opening for the smoke to spread inside the interstitial space. Therefore, when the input leakage area is 0, the training process can be skipped, and the activation time can be set as infinite.

5. Demonstration and application of AI fire prediction

5.1. Demonstration of AI prediction

The comparison of AI prediction and CFD simulation on the test set are demonstrated in Fig. 9. As observed, with the increase of HRR, both the smoke detection time and the sprinkler activation time decreases (Fig. 9a). From the point view of fire dynamics, the temperature and the amount of smoke plume is directly proportional to HRR. Therefore, it takes less time to approach the critical conditions to trigger the smoke detector and the sprinkler in fire scenarios with larger HRR. This trend is well learned by the ANN network as shown by the blue line in Fig. 9a, with prediction error less than 4 s. It can also be observed the critical HRRs to trigger the sprinkler are 40 kW (room) and 60 kW (false ceiling) according to the CFD simulation results. The HRRs less than the critical value cannot activate the sprinkler. As presented, the AI model predicts the critical HRRs successfully and the predicted activation time error is less than 15%.

With the increase of leakage area, the smoke detection time of room does not change significantly, while the detection time of false ceiling sensor decreases rapidly (Fig. 9b). This is because the room smoke detector can be triggered by the plume ceiling jet at very early stage (~10 – 15s), before the smoke approach the leakage. Furthermore, in the current study average time of the all four detectors is considered. It is possible that that first detector may trigger earlier for lower leakage area, however average time of all four detectors does not vary significantly. Therefore, the leakage area has a relatively small influence on room smoke detectors. On the contrary, the smoke needs to pass through the leakage to trigger the detectors inside the false ceiling. Larger leakage area allows smoke fills into the interstitial space more quickly, resulting in the early detection. Also, the minimum leakage area to trigger the detectors inside the false ceiling is also well predicted by the AI model (0.4 m^2 in this study).

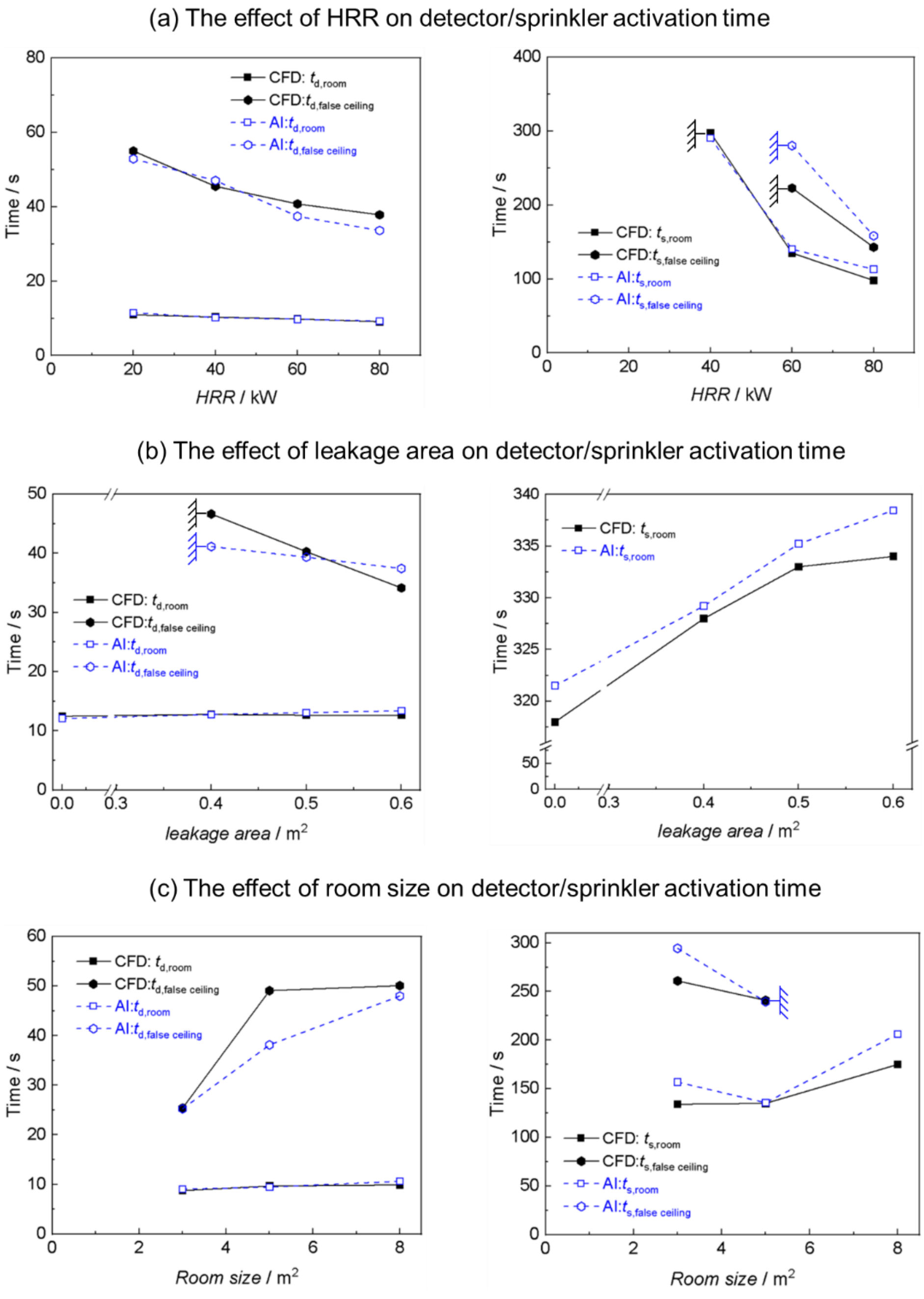

Fig. 9 ANN model prediction VS CFD simulation (a) effect of HRR (b) effect of leakage area, and (c) effect of room size, in which the test cases are not included in the training and validation set.

Moreover, it can be observed that the prediction error for the false ceiling detections is larger than room ones. In fact, the detectors inside the false ceiling are not activated in some scenarios. Therefore, the number of valid cases of false ceiling scenarios is smaller than that of room scenarios to train the ANN model. In other words, there is less knowledge about the false ceiling smoke scenarios in the training database, and thus the AI model performs better for the prediction of room smoke detection than that of false ceiling smoke detection. As for the sprinkler activation time, the AI prediction also shows a good agreement with the CFD simulation with relative error of around 10 %.

The room size also shows a significant impact on the smoke detection time of the detectors inside the false ceiling, the average detection time increases from 25 s to 50 s when the room size increases from 3 m^2 to 8 m^2. The room size has a lower impact on the average smoke detection time of the room sensor, as shown in Fig. 9c. As discussed, the activation of the room smoke detector depends on the ceiling jet process, which is only affected by the relative location of the fire source and the detectors, but the activation of the false ceiling detector is also affected by the smoke accumulation process, which heavily depends on the room size. Meanwhile, it can be observed that both the smoke detection time and the sprinkler activation time, as well as the critical room size value can be well predicted by the proposed ANN model.

The overall performance of the proposed ANN model on the predictions of smoke detection time and sprinkler activation time are presented in Fig. 10. As observed, the AI model shows an overall excellent agreement with the CFD simulation results with a relative prediction error no more than ±15 %. However, it should be noted the absolute error for the sprinkler activation time prediction (< 50 s) is larger than that of smoke detection time (< 10 s).

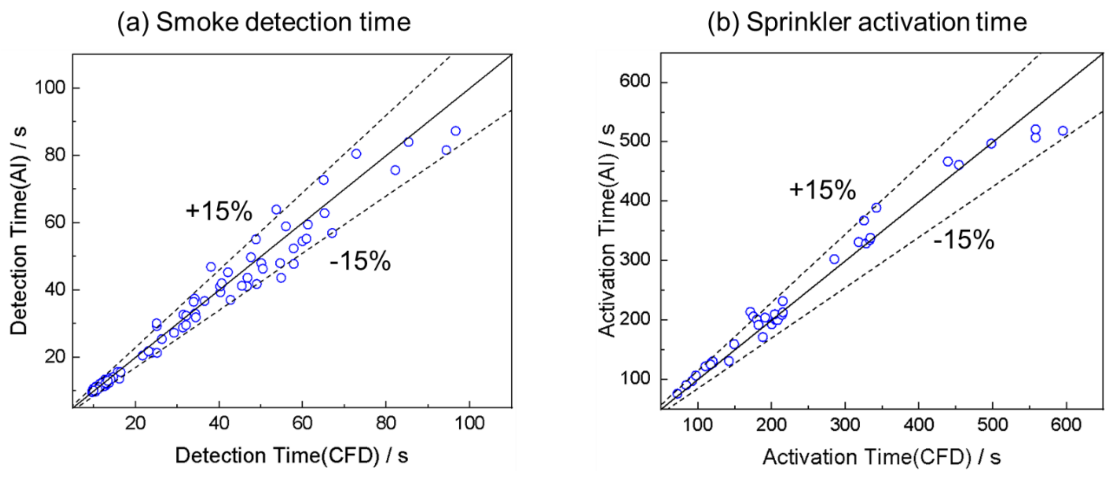

Fig. 10 Overall performance of the ANN on the predictions of (a) Smoke detection time, and (b) Sprinkler activation time

The difference may be caused by the following reasons: On the one hand, the sprinkler is more difficult to be activated than the smoke detector. It means that only smoke detectors are triggered while the sprinklers are not in many case. Therefore, there are more valid samples of smoke detection scenarios than the sprinkler activation scenarios in the database. On the other hand, it's the nature that larger uncertainty exists for a system with strong non-linear features with the increase of running time, such as the fire. Therefore, forecasting the smoke detection time (at tens of seconds level) is naturally easier than the prediction of sprinkler activation time (at hundreds of seconds level). The difference will be carefully covered in the future with more training cases and the introduction of physical knowledge to the AI mode.

Compared with CFD model, which solves the partial difference equations using numerical method, the complicated training process of the AI model 1is completed before the model was applied. The proposed model can realize super-fast prediction of critical activation times within ~1s while it takes several hours for running CFD code to solve the same fire scenario with similar results. Therefore, the proposed ANN model can significantly reduce the evaluation time and paving the way for future fire safety design and smart firefighting operations.

5.2. Smart design by machine learning

As discussed in section 2.2, designers aim to lower the RSET in order to achieve their design objectives with a reduced ASET. The RSET includes the time of detection, which can be determined from the AI trained model (presented in this paper) for the any fire scenarios. Furthermore, by changing different perimeters such as leakage area, ventilation, height of the false ceiling and so on, the time of detection can be evaluated that allows the designer to reduce the RSET. It is worth noting that the ASET must account for the escape route, the detection time of a fire in the false ceiling can provide an indication of how quickly smoke and fire may spread to other areas of the building.

Using the AI model, various fire scenarios, as required in the PBD approach, can be generated to determine the worst-case fire scenario. By providing input perimeters such as compartment geometry and leakage area, *'performance criteria'* can be evaluated. The AI trained model can instantly evaluate the FED values in the room, false ceilings, remote regions, or corridors. Furthermore, it can incorporate any changes in a compartment during the various stages of a project.

Some prescriptive standards, such as NFPA 13, require to install sprinklers above the false ceiling (interstitial space) if the open area is above certain limit (25% of the total area of the ceiling in the case of NFPA 13 [1]). However, there is no requirement for sprinklers if the area is lower. PBD provides the flexibility to the designer to determine the requirement of the sprinklers, the AI trained models can evaluate if the smoke is moving in other parts of the building and making the situation untenable. If the FED is lower and visibility is higher than the required values, the sprinklers can be omitted from the design.

The detection of the fire in the false ceiling is vital for determining the probable 'spread of fire' and firefighting operation. The information obtained from the AI trained model of the building can tell firefighters the time when the fire or smoke would reach false ceiling and other parts of the building. A-priori information of fire location can assist firefighters in improvising their firefighting strategies and increase the probability of success of firefighting process and reducing the risk of casualties associated with firefighters [13]. Next section discusses more about the forecasting of the events that can help the fire emergency.

5.3. Data-driven forecast of false ceiling fire

A fire incident can be a breakdown in multiple layers of fire safety measures. Despite following the latest fire safety standards in design and utilising proper listed equipment, buildings can still experience failures during fires, as observed in many fire accidents. Some of the primary causes of fire incidents include inadequate maintenance, negligence in filling construction gaps (wall or ceiling penetration), or the use of inappropriate fire rated materials, which compromise the integrity of false ceiling. When a fire occurs in a building, hundreds of events may occur if the fire is not controlled during the initial stages. A detailed library of critical events is produced by Khan et al. [13] using the available literature, codes and standards, incident reports, and interviewing firefighters. This study focuses on the critical events associated with false ceilings. Some of the major critical events are presented in Fig. 11.

Fig. 11 shows the chain of events that may occur in a building if the fire reaches above the false ceiling due to leakage or failure. Failure of a false ceiling can be considered a pre-cursor event, which can lead to other critical events (Fig. 11). As discussed earlier, once the fire reaches above the false ceiling, the situation may become more critical and dangerous, and it makes the firefighting process more difficult and complex. A precursor event may lead to further pre-cursor or critical events, the severity of these events can be presented by colours (orange and red represent the situation as severe and very severe, respectively). As shown in Fig. 11 (as observed in the experiment [4]), through a false ceiling, the fire or smoke can reach the intestinal space above the false ceiling, which can lead to many events. For example, the fire may travel all over the floor (travelling fire behaviour) in an open interstitial space which may lead the structural damage such as the collapse of slabs, beams as observed in case of the Plasco Building fire accident [3,9,57]. Multi-compartment fire is also another adverse effect of false ceiling fires, which makes more difficult to control the fire. As observed in the experiment, the smoke can reach corridors which can impede the evacuation of the occupants and may delay the firefighting process as well.

Firefighting is an intensive strenuous physical activity but same time it may require making instant decisions and reviewing or revising the risk analysis based on real-time information (known as Dynamic Risk Analysis [DRA]). A prediction on the status of fire can provide probability of the fire and smoke spread. Such information can help in determining the critical events that may occur inside the building [13]. A-priori information of an event provides firefighters more time to evaluate the situation and make DRA more effective in a life-threatening situation. A highly sophisticated AI model - developed based on large database - can propose a solution or guide the firefighter in making effective and timely decisions. This paper presents how a large database can be created to develop an AI model that can be used to predict the future events associated with the false ceilings. The next sub-section presents the framework describing how data driven AI models can be used in "Smart firefighting".

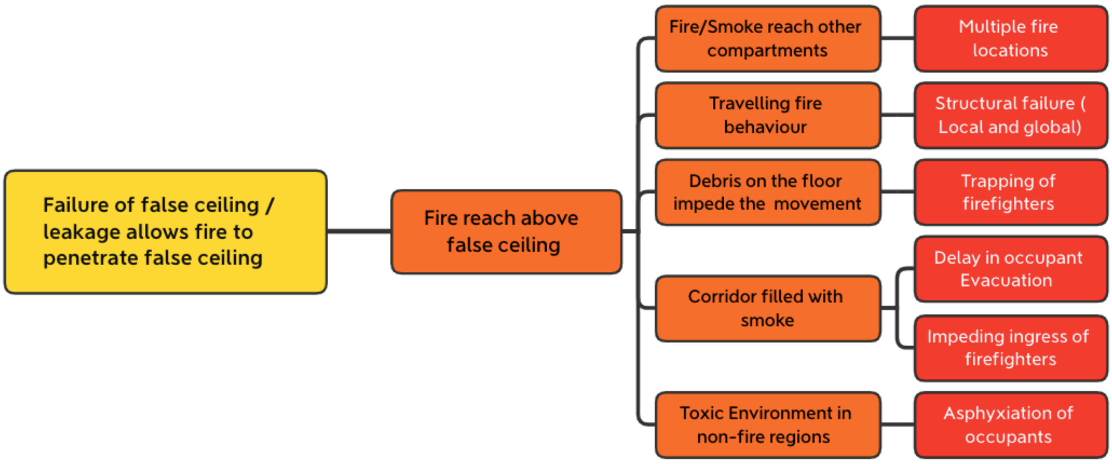

Fig. 11 Some of the critical events associated to failure of false ceiling

Since the recent boom in the field of big data and deep learning, AI approaches, as well as other cutting-edge technologies such as remote monitoring, high-resolution sensor, high-speed computation, and data-driven methods, have been increasingly applied in fire safety engineering. Currently, the application of AI in fire engineering and firefighting is still relatively less mature. Nevertheless, AI codes in the future are expected to be customized and optimized to benefit firefighting with a more user-friendly interface. The predictions of critical events can be derived from a purely data-driven approach using heuristic, AI, and machine learning technologies to provide forecasts by matching real-time data streams with a large database of stored simulations. Together with the development of building IoT (*Internet of Things*) and digital twin, a mature AI-driven fire forecast engine can be implemented into a building to identify and forecast fire scenes and support smart firefighting. Fig. 12 explains how *real-time* data can be used for forecasting critical events, which can further be used for smart firefighting. As shown in Fig. 12, real time information of the fire can be obtained from the IoT devices that can be used to predict the events from the trained AI model. The estimated time and severity of events can be displaced on the user interface. This paper also provides the methodology to develop an AI model for predicting the events associate with the false ceilings (Fig. 11).

The current study suggests that having architectural information of a compartment and detection time of the fire can guide the firefighters by providing the location of the fire and estimated time of the fire reaching the false ceiling. Some of the information (not limited to) that can help firefighters for effective DRA are listed below.

- Real time status of the building in fire
- The time when the fire may reach the false ceiling.
- Direction and spread rate of the fire in different parts of the building.

- Estimation of the fire size (from predictive rime).
- Forecasting of critical firevevents such as failure of false and main ceilings and structural changes.

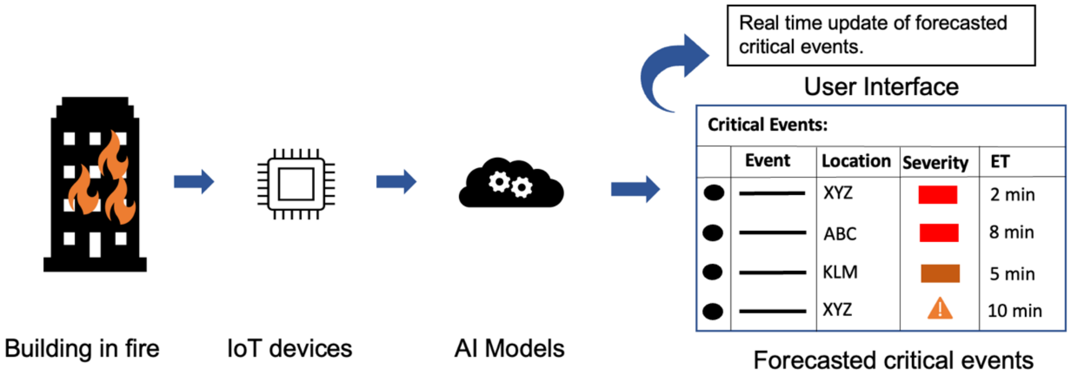

Fig. 12. Framework for forecasting of the critical events.

6. Conclusions

This numerical study evaluates the fire detection time in the fire room and above the false ceiling. The effect of various parameters - such as HRR, leakage area, room size, fire location and ceiling height – on the detection time and sprinkler activation is studied. Using all these parameters, a large database of numerical results is generated to train an AI model. The AI model is capable of predicting the time of detector activation by knowing the compartment geometry (including total leakage area) and fire location. The AI trained model can generate multiple fire scenarios and assess the effectiveness of their design in each scenario by determining the ASET and the parameters that can reduce the detection time. The trained model is capable of determining the visibility and FED of thermal effects and species concentration which are critical for performance-based design. Lower value of HRR is taken in the current study to evaluate the detection time. However, for a fire size of larger HRR, the FED such as letal concentration of poisonous gases and reduction of visibility required by codes and standard may achieve in early stages and affect the tenability of multiple compartments including corridors

The paper further proposed a framework to predict the activation time of the detector and sprinkler using IoT devices to forecast the possible fire location and fire (and smoke) spread. Having information from the IoT devices, the trained AI model can provide the information of critical events associated with the false ceilings such as the estimated time when fire may reach the false ceiling, fire spread to other compartments or prediction of structural failures. The methodology presented in this paper can be a step towards the smart firefighting, which can assist the firefighters in a life threating situation. It accomplishes this by enhancing the overall robustness of emergency response processes and enabling dynamic risk assessment based on event predictions.

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