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Smart Performance-Based Design for Building Fire Safety: Prediction of Smoke Motion via AI

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Abstract: The performance-based design (PBD) has been widely adopted for building fire safety over the last three decades, but it requires a laborious and costly process of design and approval. This work presents a smart framework for fire-engineering PBD to predict the smoke motion and the Available Safe Egress Time (ASET) in the atrium by Artificial Intelligence (AI). A CFD database of visibility profile in atrium fires is established, including various fire scenarios, atrium volumes, and ventilation conditions. After the database is trained with the transposed convolutional neural network (TCNN), the AI model can accurately predict the smoke visibility profile and ASET in the atrium fire. Compared to conventional CFD-based PBD by professional fire engineers, AI method provides more consistent and reliable results within a much shorter time. This research verified the feasibility of using AI in fire-engineering PBD, which may reduce the time and cost in creating a fire-safety built environment.

Keywords: *Building Safety; Deep Learning; ASET & RSET; CFD; Smart Firefighting*

Abbreviations

AI	artificial intelligence	HRR	heat release rate
AFFL	above finished floor level	LSTM	long short-term memory
AHJ	authority having jurisdiction	MSE	mean squared error
ANN	artificial neural networks	PBD	performance-based design
ASET	available Safe Egress Time	RNN	recurrent neural network
CFD	computational fluid dynamics	RSET	required Safe Egress Time
CNN	convolutional neural network	SURF	super real-time forecast
FDS	fire dynamics simulator	TCNN	transposed convolutional neural network

1. Introduction

1.1. Background of Performance-based design

Performance-based design (PBD), as an engineering approach, goes beyond prescriptive code requirements and has been widely adopted globally [1–6]. In the domain of building and environment, the performance-based option brings design flexibility to the building by introducing acceptable methodologies, analysis tool, and performance criteria. Then, the built environment can meet specified design goals and objectives of fire and life safety, property protection, business continuity, and environmental protection. PBD for fire safety was initiated from the 1970s to the early 1990s. After years of development, building codes and regulators have gradually adopted the performance-based design as compensation for prescriptive code design [4,7,8].

From the Great Fire of London in 1666 to the recent Grenfell Tower fire in 2017, devastating fire events have always been the primary driving factor for the establishment of building fire code [9,10]. Along with the development of building fire safety research and insurance policy since the 1950s, more sophisticated prescriptive fire-safety standards, codes, and regulations have promogulated and enforced (Fig. 1). Nevertheless, for the past three decades, the emerging innovative architectural design features and the invention of new materials [3,4] incentivizes new fire research and engineering tools, such as the computational fluid dynamics (CFD) and evacuation model. The framework of performance-based engineering design has been developed and incorporated in the design handbook, code, and regulation [11–14]. Subject to the design objective, various approaches could be adopted to achieve the equivalent level of fire safety or attain the stated performance, such as structural fire analysis, or external fire spread prevention analysis. More flexible concepts and acceptance criteria of PBD, like the available safe egress time (ASET) and the required safe egress time (RSET), have been proposed to justify the safety of the occupants' evacuation in the fire event from the life and safety perspective [12,15–17].

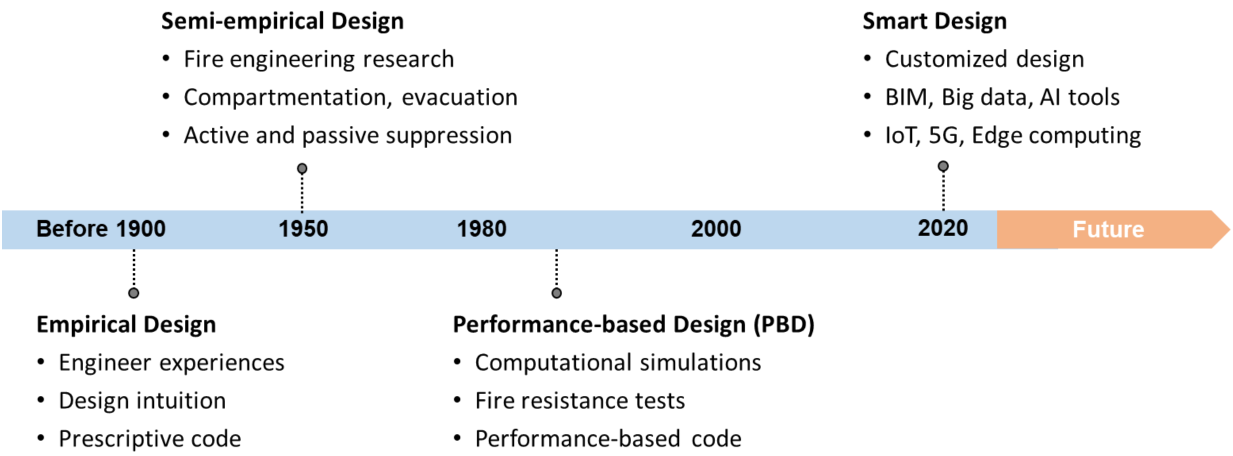

Fig. 1. The evolution of building fire safety code and design.

For a typical fire-engineering PBD, the authorized person or the engineering-consulting company needs to submit the developed fire strategy and documentation to the authority having jurisdiction (AHJ), e.g., the local fire services department or buildings department, for the final approval. Many design variables affect the analysis, and results differ on a case-by-case basis, so both designers and AHJ need to have extensive experiences and scientific knowledge to evaluate the PBD [18]. Despite that PBD has been widely applied for building fire safety since the 21st century, it is far from perfect, and there are three significant issues.

(1) Enormous time and human resources are needed for each PBD case in the design, documenting, review, and approval processes. Sometimes, these processes for challenging architectural and functional designs can repeat for several rounds and last for years [8,19].
(2) Many criteria used in PBD were established in limited amounts of early fire tests and numerical simulations, so that their reliability and feasibility for the new built environment are questionable [20,21]. Like the prescriptive code, once the paradigm of PBD is established, there is often little motivation to further investigate the validation of PBD unless another devastating fire occurs.
(3) Professional fire engineers and designers develop "tricks," e.g., tunning fire modeling parameters and hide poor-performance cases, to bypass the scrutiny of AHJ, which increases the chance of disastrous fire events.

To solve these issues, the emerging development of big data and artificial intelligence (AI) may provide new design approaches and solutions for both designers and AHJ. Potentially, the powerful pattern matching capacity of deep learning could reduce the unnecessarily repeated workload, improve the building fire safety, and reduce the construction cost.

1.2. AI-based fire engineering

The concept of artificial intelligence (AI) was arguably first proposed in a workshop held in Dartmouth College in 1956 to handle computer-based language understanding, storage of data, and pattern matching [22]. The emerging deep-learning models imitate the human brain, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [23,24]. Compared with conventional AI models, such as machine learning models, deep learning models require more data to learn hidden features from the massive data automatically.

Over the past decade, smart-firefighting techniques of AI algorithm, IoT, and sensors are gradually adopted [25,26], particularly in the fire behaviors and risk assessments [27–29], compartment fire [23,30–36] and tunnel fire [37,38]. Hodges *et al.* [30,31] used a transpose convolutional neural network (TCNN) and simulating results conducted by FDS to predict the temperature distribution inside compartment rooms. Lee *et al.* [39] compared the performance of various models and demonstrated the feasibility of their faster regional CNNs in detecting fire, meanwhile reducing false positives. In nature, all existing AI models need to be fine-tuned before being applied to solve problems in practice. Often this is realized through a large number of training iterations on a big database. Thus, a well-structured fire database is also a pre-requirement of AI applications in fire engineering. For example, Naser *et al.* [40] built up a database of fire tests on timber structures and predicted the fire resistance of timber structures via AI model. The recently established tunnel-fire database not only predicted the location and size of fire source [37] and critical fire events (e.g., critical ventilation velocity) [38], but also enabled the super real-time forecast (SURF) of the future evolution of fire fields [41]. So far, most of the AI application in fire engineering focused on the fire detection and forecast. Arjan *et al*. [33] adopted a logistic regression model to predict the occurrence of flashover in a compartment using the information of fuel thickness, burning intensity and duration. The probabilistic methods have also been applied in evaluating the current fire safety design using [42–44]. Naser *et al*. [45–48] applied AI methods in the prediction of structural fire performance. They also developed machine learning algorithms to forecast the spalling of concrete components and degradation of steel properties under fire incidents. To the best of the authors' knowledge, very few studies have explored the use of AI methods, especially the deep-learning methods, for the building fire safety at the design stage.

This paper aims to explore the feasibility of AI methods in the fire safety design of the atrium. A database of 280 numerical atrium-fire cases is developed for different atrium dimensions, as well as fire sizes and ventilation conditions. The PBD concept of ASET with the corresponding acceptance criteria, e.g., visibility and smoke-layer height, is adopted to train the AI model and predict the validity of ASET in randomly selected cases. In addition, six professional fire engineers are invited to conduct case studies with both their intuition and the PBD with CFD tools as a regular consultancy task. Finally, comparisons of performance are made between human professionals and AI agents to demonstrate the proposed AI approaches.

2. Framework for smart ASET assessment

2.1. Conventional PBD for ASET and RSET

One acceptable PBD concept of building fire safety involves the occupants' evacuation in the fire event is the *evacuation time analysis*, that is, comparing the ASET versus the RSET. The ASET is the time reaching the onset of untenable criteria for occupants, so it is often derived based on the prediction of fire and smoke behavior in a built compartment [15]. The RSET is the time that allows occupants to leave the fire-affected area to a safe place [12]. To ensure that occupants can safely egress before reaching untenable conditions, ASET > RSET is the minimum requirement. In general, a reasonable safety margin, i.e., the difference between ASET and RSET, is also required, which could be considered as a safety factor in fire-engineering design.

For the design of large and complex buildings, it is neither possible to conduct real-scale tests nor reliable to use simple empirical correlation for obtaining the ASET and RSET. Thus, the ASET can only be determined by the numerical fire simulations (e.g., via the zone model or CFD model), and the RSET can be simulated by the evacuation modeling. Today, commercial software has been widely used in fire engineering consultancy tasks to obtain ASET and RSET. To determine the ASET, acceptance criteria have to be quantified, for example, considering the smoke filling progress in a typical compartment fire and the level of exposure to untenable conditions [19]. Table 1 lists the acceptance criteria for tenable conditions in Hong Kong [16], which also refers to the handbook, standard, and code in other countries and regions, e.g., PD 7974-6 [15,16]. Note that the analysis can vary subject to the complexity of geometry and the design of fire size, ventilation system, and plume entrainment with openings [49].

Table 1. Acceptance Criteria for tenable conditions [16].

Life Safety Parameter	Tenability Acceptance Limit
Design Smoke Clear Height	2.0 m AFFL of occupied level
Visibility	≥ 10 m of visibility
Radiant Heat Exposure	2.5 kW/m^2
Air Temperature	≤ 60 °C
Carbon Monoxide Concentration	≤ 1000 ppm

Usually, modeling results of smoke motion and height profile should be presented to AHJ to illustrate the assessment of ASET. It is well known that different engineers and consulting teams can provide very different values of ASET. Such a variation of ASET is unavoidable, because fire engineers can conduct personalized fire modeling and make their own judgment and interpretation on the results considering the rationale of life and safety. On the other hand, AHJ may question the adopted performance design criteria and technical issues, such as the validation of the designed fire size, fuel type and arrangement, smoke properties, or the approach for quantifying the proposed objectives [8]. For complex and challenging cases, AHJ sometimes requests the source code or input files or a third party to double-check the validity and reliability of modeled ASET.

Fig. 2(a) illustrates the flow diagram of the design and approval processes of ASET in a conventional PBD. In general, it includes three stages, (1) problem identification and modeling design, (2) CFD-based fire modeling to evaluate results and justify performance, and (3) authority approval. In many cases, the conventional design process could be repeated for several rounds and last for years due to design changes or addressing AHJ comments, resulting in the uncertainty of the construction program.

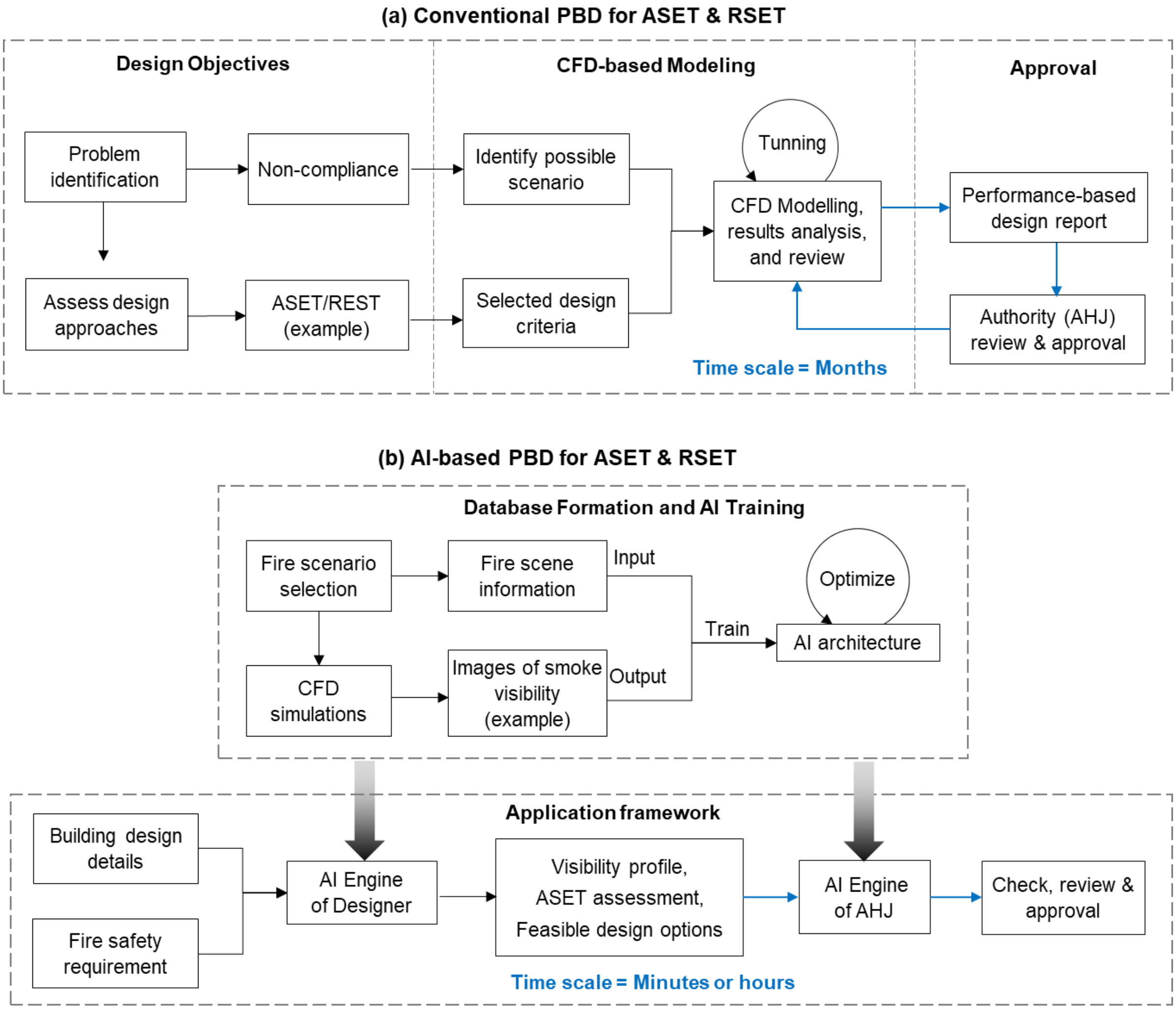

Fig. 2. (a) Conventional performance-based design (PBD), and (b) AI framework for the PBD for ASET and RSET assessment.

2.2. *AI method for ASET*

Fig. 2(b) illustrates the framework of the proposed AI-based PBD. The foundation of the AI methods is the pre-establishment of a big database and pre-training of the AI model. Using the ASET in the atrium fire as the example, it would be influenced by multiple factors, including the volume and geometry of the atrium, fire size in terms of HRR, and the ventilation condition of the atrium design. All these parameters are considered in constructing a fire scenario library representing the potential atrium fire scenarios. The evolvement of the smoke visibility with time inside the atriums are then examined via numerical simulations. The simulated results of all fire scenarios are collected to form a large database for the training of the AI model, which is optimized to achieve the best performance. Although it takes a long time to form a big database of fires in large open spaces and train the AI model, once accomplished, the trained AI model can be packed into a software tool for direct use by designers and AHJ. Moreover, the AI tool can be further updated with more data and more advanced algorithms. Such a process is similar to the development and verification of CFD fire-modeling tools, which have been commercialized after many years of developments and updates.

The application of AI tools in the PBD also includes three stages, which is further explained with the example of ASET in the atrium fire.

(1) *Preprocessing and input*. Key input factors, such as fire HRR, atrium, and smoke-ventilation designs, are chosen. Like the conventional PBD, some approximations could be made, e.g., the shape of the atrium and fire growth rate.

(2) *AI Prediction*. Given the input information, the fine-tuned AI model is capable of predicting the development of smoke motion and visibility profile for the atrium fire. Ideally, the option of the AI model is in the time scale of seconds.

(3) *Output and application*. The output of the AI model could be the time evolution of smoke/visibility profiles or a specific value of ASET based on the selected PBD code.

Moreover, the AI engine can determine the possible range of each design parameter, e.g., the maximum fire size under the given ventilation, and provide optimal design options. Then, the laborious and costly trial-and-error process of CFD modeling for every consulting cases can be avoided. On the other hand, the AHJ can also apply the proposed AI tool to quickly check the reliability of the conventional PBD without conducting similar CFD fire modeling processes. Thus, the design and review process can be reduced from months for convection PBD to hours and minutes for AI-based PBD.

3. Case study of atrium fire

In this work, the fire scenario in the large-space atrium, probably the most common fire engineering consultancy case, is chosen to demonstrate the AI-based PBD design for ASET. So far, extensive fire tests and numerical research have been conducted to understand the fire growth and smoke movement, as well as the effectiveness of the smoke ventilation system [13–17]. Once a fire occurs, the smoke-layer height descends inside the atrium along with the increase of time, which can be observed in both fire tests and numerical simulations. Thus, the ASET can be determined by the height profile of the smoke layer and visibility.

In general, occupants inside an enclosure should evacuate from the fire-affected zone to a relatively safe place or adjacent unaffected zone. Thus, at least 10-30 min (RSET) are needed to ensure a safe egress, subject to practice approval by AHJ, and ASET > RSET should be satisfied. In this work, the Hong Kong Building code (Table 1 [16]) and the ASET of 20 min are adopted to assess the performance requirement at each scenario. Based on the practical experiences, the strictest tenability criterion is that the *occupied region up to 2.0 m above the finished floor level (*AFFL*) with visibility above 10 m*, because it fails first before reaching the other criteria of temperature, heat flux, and CO level. Thus, such a visibility criterion will be used to define the ASET.

3.1. Numerical fire model

Like a typical consultancy task, the CFD fire model is established to simulate the atrium fire and smoke motion. Fire Dynamics Simulation (FDS) version 6.7 developed by NIST [50] was used to conduct the fire modeling and generate the numerical database. FDS, as a widely used CFD tool by fire researchers and engineers, is particularly reliable in predicting the smoke movement after it has been extensively validated by real-scale fire tests [51–55].

A simplified cuboid large open space (e.g., for a commercial building, hotel lobby, and convention hall) is chosen for the atrium model, and the floor layout is a square, as illustrated in Fig. 3. Such a simplification reduces the unnecessary variation of structure parameters and enables an easier comparison and analysis. To form a big numerical fire database and cover more possible PBD scenarios, four key parameters are varied, and their range are determined from previous studies and fire engineering practices in the performance-based design. Specifically,

(1) Height of atrium. As specified in the Hong Kong fire code [16], this value should not exceed 15 m, according. To make the artificial intelligence (AI) algorithm to be applicable in a wider range after training, a typical height of 10 m and an extreme height of 20 m is considered in simulations.

(2) Fire size (peak HRR). Past studies showed that the peak HRR of a significant fire in an atrium is between 0.56 MW and 10 MW [53,56–59], so seven values from 0.5 MW to 10 MW are selected.

(3) Length of the floor. Four values from 30 m to 90 m are determined based on the common size of real atrium designs.

(4) Smoke extraction rate: After the ranges of the above three parameters are determined, the upper limit of the ventilation of 40 m^3/s is selected by preliminary simulations that under such a high extraction rate, all the scenarios could satisfy the RSET requirement. The lower limit of the ventilation is set as 0 m^3/s, indicating that no mechanical or natural ventilation is provided. Five values from 0 m^3/s (no ventilation) to 40 m^3/s are set for different ventilation conditions.

The values of these parameters are listed in Table 2. In total, 280 fire simulation cases were conducted to form the database. Both the floor area and atrium height can change the atrium volume, which ranges from 9,000 m^3 to 162,000 m^3. According to the HK building regulation (C10.3 [16]), the fire-engineering PBD is required if the atrium volume exceeds 28,000 m^3 or the maximum height from the floor to the ceiling exceeds 15 m.

Table 2. Parameters of simulation cases.

Parameters	**Range**
HRR (MW)	0.5, 1, 2, 3, 5, 8, 10
Atrium side length (m)	30, 50, 70, 90
Atrium height (m)	10, 20
Smoke extraction rate (m^3/s)	0, 10, 20, 30, 40

The fire source is placed in the center of the atrium model. The burning materials are assumed to be a mixture of natural material (50%) and plastic compound (50%), so the soot yield is set to 0.043 g/g [60]. The heat release rate per unit area (HRRPUA) of a sprinklered fire is set as 500 kW/m^2 for typical solid fuels [59]. The fire HRR is designed with a fast growth fire rate of 0.0469 kW/s^2 as suggested by CIBSE Guide E, which reaches the peak and remains a constant value thereafter [12]. The visibility factor is defined as 8 and 3 for light-emitting and light-reflecting signs, respectively [12]. The extraction velocity on the ceiling vent is controlled by changing the mechanical smoke extraction rate. Several door openings with a height of 2 m are set on two side walls to ensure an adequate air supply to fire (see Fig. 3). The thermal boundary of domain surfaces is set as the default wall with an ambient temperature of 25 °C, which takes the heat transfer between walls and surrounding air into account. The minimum simulation time of all cases is set as 1,200 s. Multiple Z-plane and Y-plane slices are set to record the temperature or visibility contours.

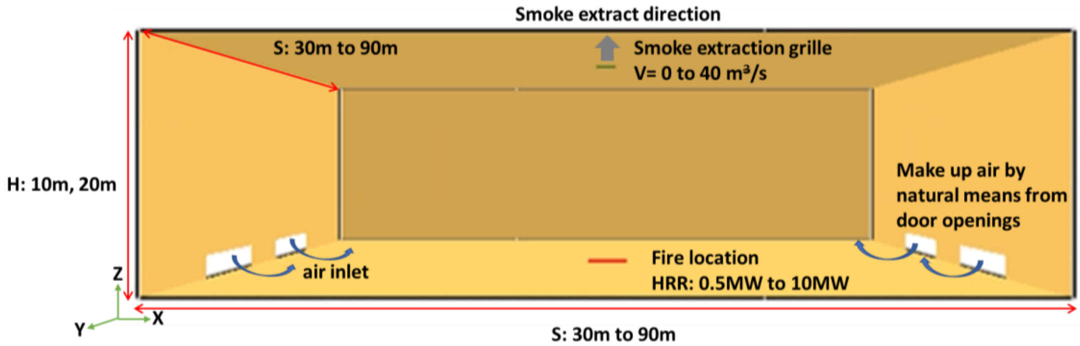

Fig. 3. Illustration of the numerical model of atrium fire and key parameters.

The mesh resolution in FDS simulation can be described in terms of the non-dimensional expression ($D^*/\delta x$), where D^* is a characteristic fire diameter and δx is the control volume size. The recommended value for involving buoyant plumes suggested by the FDS user's guide is to be within the range from $D^*/4$ to $D^*/16$, which considered the accurate prediction of temperature and the smoke movement [61]. The same grid size of 0.4 m was adopted for the entire atrium to facilitates the subsequent extraction of simualtion reuslts from the postprocessing software and the construction of the training database. No extended domain was set to mitigate the impact of the openings for each model. The cell number of the model ranges from 140,625 for 9,000 m^3 to 2,531,250 for 162,000 m^3. Reducing the cell size by a factor of two gives no significant difference in results, as demonstrated in Fig. A1. Thus, numerical calculations are sufficiently resolved. With a 32-core server, the computational time varies from 15 h to 48 h, subject to the atrium volume and fire scenario of each case.

3.2. Database of smoke motion and ASET

The time-dependent visibility profile (or smoke profile) of simulated atrium fires are then extracted to generate a big database and train the AI model (Fig. 4). The input parameters in the CFD model (building and fire information), including atrium floor area and height, fire size in terms of HRR and smoke extraction rate, are also taken as the input of the AI model. In view of the unsteady state nature of the smoke movement during a fire, the time after the ignition is regarded as another parameter of the input. Large datasheets shown at the lower left of Fig. 4 are then formed, with each column representing one parameter of the input and each row representing one input vector.

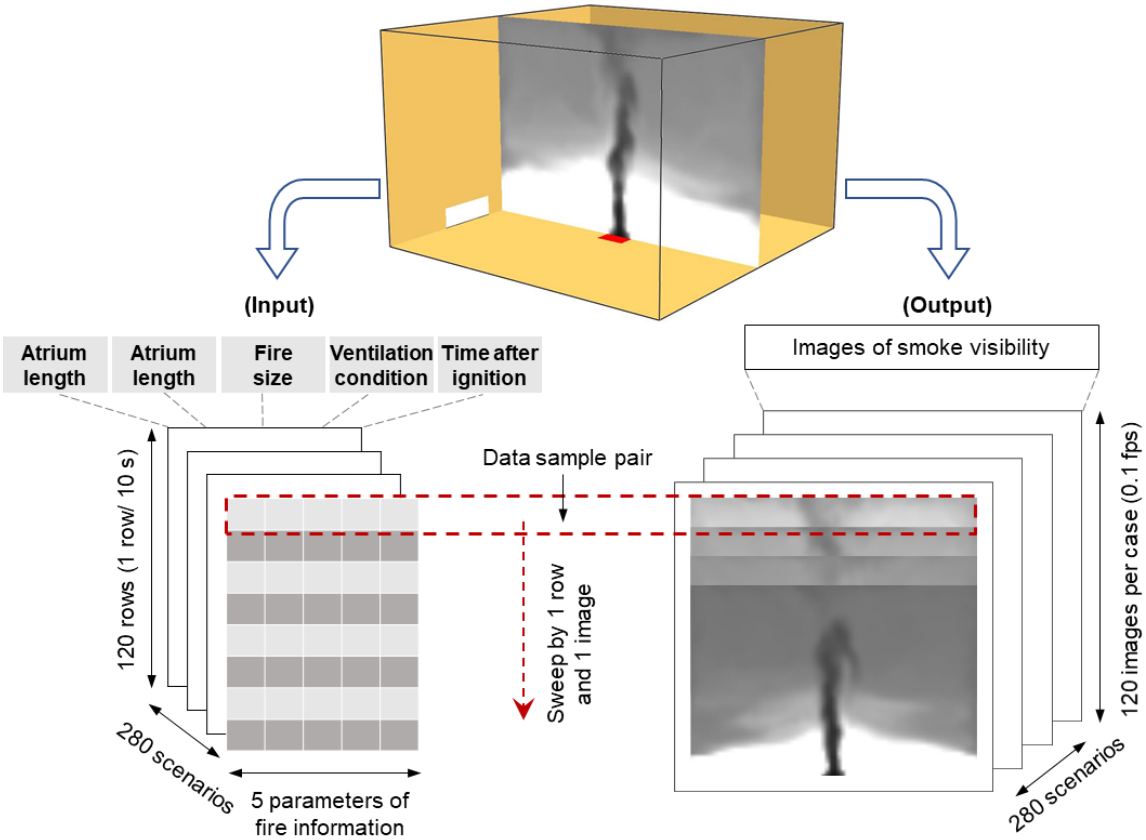

Fig. 4. Database generation from modeling results which is divided into input and output to train the AI model.

The visibility data evolving with the time recorded by the defined vertical slice located at the middle of the atrium in the direction of the *y*-axis is exported from the modeling results. A middleware "fds2ascii" is used to dump the raw simulation data from the post-processing software Smokeview. To accelerate the simulation speed for scenarios of large atrium volume, the computational space is partitioned into multiple meshes for parallel computing, which causes the separate storage of slice data in multiple meshes. In these cases, the data on a slice from all the meshes are merged to a frame matrix in line with their spatial locations. The data matrix from all the simulations is then resized into the same dimensions of (50 × 50) cells in both directions. The matrix shaded for visualization at the lower right of Fig. 4 serves as the target output of the AI model. A fire duration of 1,200 s and an export frequency of 1 frame every 10 s produce 120 samples for one scenario. In total, there are 33,600 samples for all 280 atrium fire scenarios.

One input vector, together with one output matrix, corresponding to the given fire scenario and time, forms one training sample pair. Each column of the input sheet and each frame of the output matrix is normalized into the same range [0, 1] with the min-max normalization function [62]. This is to prevent the condition whose features have more extensive ranges from dominating the computation of similarity [48]. Afterward, the sample pairs are randomly disordered and divided into training, validation, and test datasets with a ratio of 0.6, 0.2, and 0.2, respectively. The training dataset is used to train the model, the validation dataset is to evaluate the fitted model while training, and the test dataset is to estimate the quality of the fitted model on unseen samples after training.

3.3. *AI algorithm and training*

The AI model is assumed to have acquired zero expertise knowledge about the calculation of visibility inside an atrium at the time of establishment, while it will learn how to accomplish this specific task through a continuous training process. The capability of a transposed convolutional neural network (TCNN) in obtaining the spatially resolved temperature at a steady-state inside an enclosure has been demonstrated by previous researchers [31,37]. However, it is still unknown whether the AI algorithm can forecast the smoke visibility inside a large volume atrium with complex fire and ventilation scenarios. More significantly, there has been little study on the prediction of the time-dependent (or transient) smoke flow behavior of fire. Considering the similar target of obtaining an image, the ability of the TCNN model in tracking the development of visuality induced by atrium fire is explored.

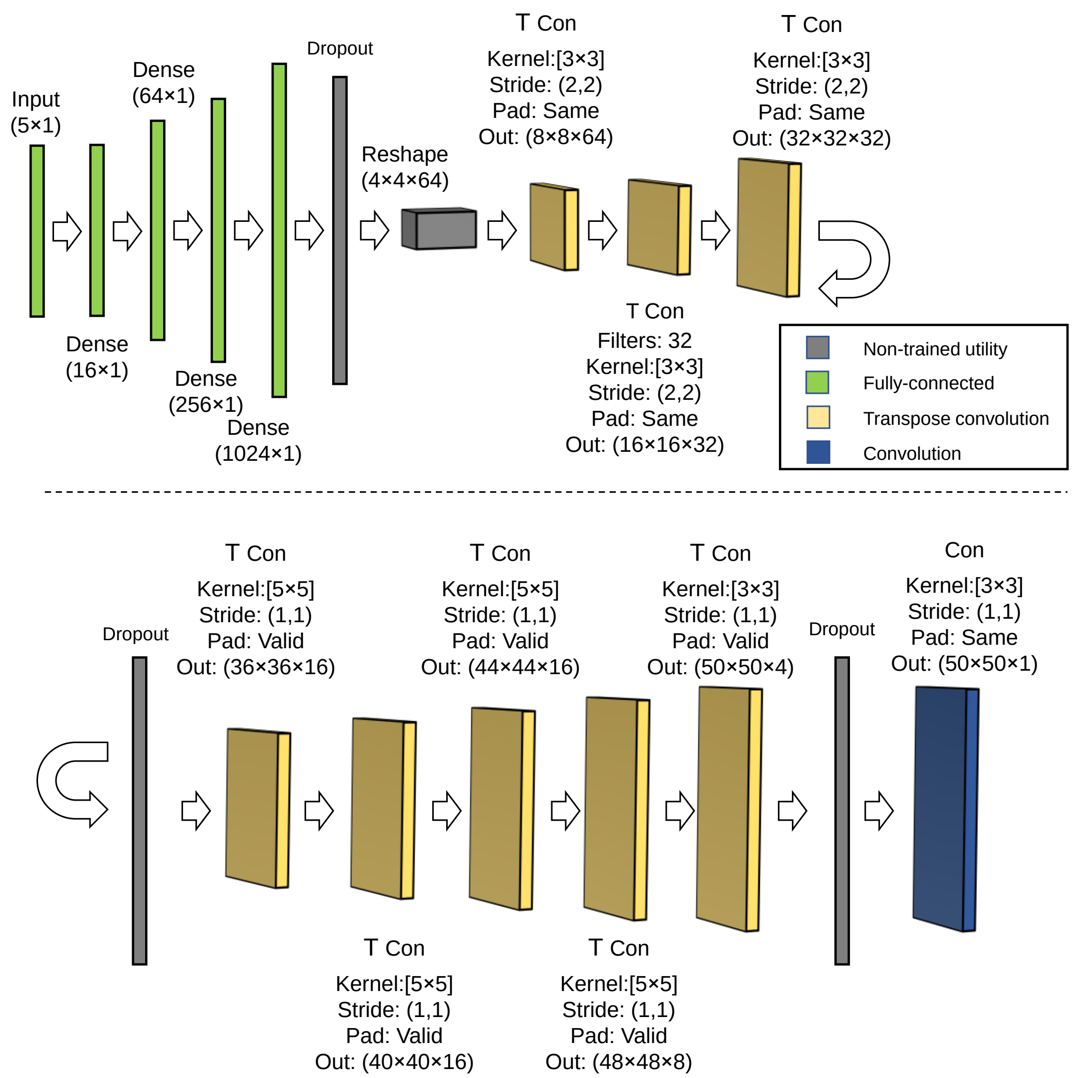

Fig. 5. The architecture of the proposed AI model.

Fig. 5 shows the detailed architecture of the proposed deep-learning AI model, consisting of a total of 18 layers in total, among which 13 layers of coefficients can be updated through the training process. The five values of the input vector are read by the input layer in sequence, as shown in Fig. 4. The information hidden inside the input is then enriched by the following 4 dense layers. After being expanded into a dimension of 1024, the vector is reshaped into a box having a size of (4×4×64) while keeping the values in the vector unchanged. Then, the data are upsampled through 8 TCNN layers and 1 CNN layer to generate an image with 50 pixels in both dimensions. Note that the fixed structure of the AI model during training determines that all the generated images have all these dimensions, regardless of the height and the length of an atrium. The generated image can then be compared with the actual one of the outputs (Fig. 4), and then, the AI model is trained to minimize their difference. Various padding scheme and stride parameters are set for these layers to continuously enlarge the dimension of the image. Three dropout layers are used to alleviate over-fitting during training.

Although a better performance can generally be achieved with a deeper learning model, the inherent large volume of layers, neurons, and weights can make it rather difficult to train and adjust a sophisticated model. The super parameters of the number of layers, the type of each layer, the dimensions of the input and output shown in Fig. 5 are determined by preliminary studies. The weights of each layer will be updated through the training process. The training efficiency and final performance depend much on the selected functions. In this study, the nonlinear activation function "tanh"

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

which is adopted for each training layer to map the input into a range (-1, 1). The loss function "mean squared error" (MSE) is chosen as the loss between actual and predicted values. MSE is defined as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{2}$$

where n is the dimension of the vector $\boldsymbol{Y}$ compared, and Y_i and $\hat{Y}_i$ are actual and AI predicted values of the i-th data point, respectively. "adam" is often a default setting for regressions and is assigned as the optimizer to find the path of minimizing the loss. It should be noted that alternative functions can also be adopted where applicable, while they are not thoroughly explored here considering the already achieved high training efficiency. The coefficient of determination R^2 was adopted to evaluate the trained model. R^2 is defined as

$$R^2 = 1 - \frac{SS_{tot}}{SS_{res}} \tag{3}$$

in which SS_{tot} is the total summary of the squares $\sum_{i=1}^{n}(Y_i - \bar{Y})^2$ where $\bar{Y}$ is the mean of the actual values $\frac{1}{n}\sum_{i=1}^{n} Y_i$, and SS_{res} is the summary of the squares of the residual $\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$. In addition, R^2 is a scale-free parameter, meaning that it is independent of the exact differences of the predictions. The performance of various models can be directly compared by this value. A higher indicates a better performance of the model in prediction. The theoretically highest value of R^2 is 1, when the predicted values perfectly match the actual values.

During the training process, samples are not read into the AI model to update the coefficients individually in sequence. Also, they will not be taken at the same time since the physical memory of the computer or server for training the AI model is often limited. Instead, to balance the training efficiency and solving stability, all the samples are preferably grouped into several mini-batches. For the current work, a server with 32 CPU cores and 124 GB physical memories is adopted to run the AI training. All the 20,160 (i.e., 60% of 33,600) samples are divided into 20 batches, with each batch having 1008 samples. With these settings, training of 400 epochs costs about 27 h.

4. Results and discussions

4.1. Training loss and accuracy

Fig. 6 shows the quality of training and validation, where the evolvements of the loss are defined in Eq. (2), and the coefficient of determination R^2 is defined in Eq. (3). The loss decreases with the number of training epochs on the training dataset to a near-constant value of 0.0065. As expected, the training accuracy goes up to an extremely high level immediately after the starting of the training, while no apparent rise is observed after 200 epochs, indicating that the model has almost converged and it is rational to terminate the training process at epochs of 400. Finally, R^2 on the training dataset converges to 95%. The high score approaching 100% indicates the high performance of the trained model on the forecasting of spatially resolved smoke visibility from the right start to 20 min after ignition. The phenomenon that both loss and accuracy on the validation dataset are comparable to those on the training dataset proves that the overfitting was not incurred. A close checking reveals that better performance on the validating dataset is observed, which is mainly due to the setting of the dropout layers. The slight fluctuations existing on all the curves are expected results of machine learning [65,66].

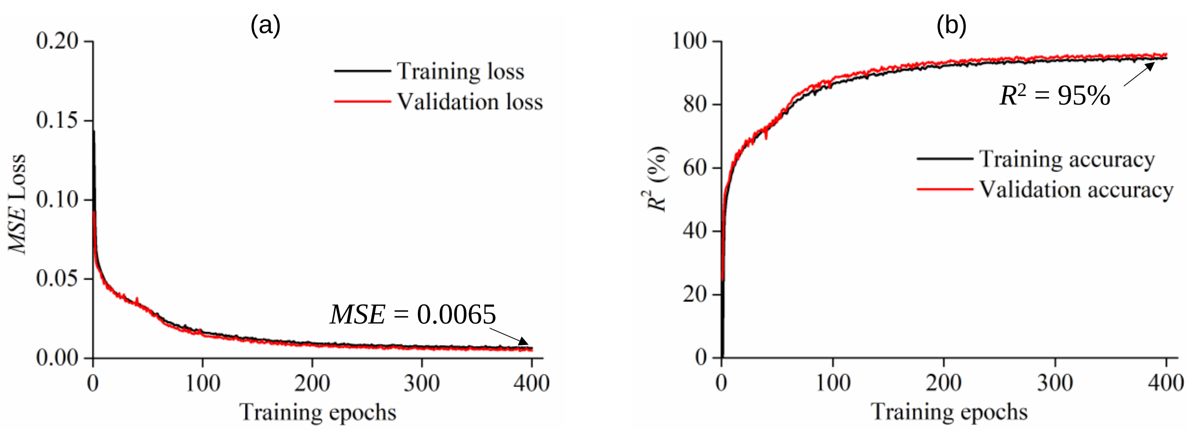

Fig. 6. The evolvements of training and validation (a) loss and (b) R^2 with the training epochs.

4.2. Spatially resolved smoke visibility

The forecasting quality of the AI model is checked in this section. Fig. 7 compares the actual (CFD simulation) and predicted (AI model) distribution of smoke visibility inside the atrium at various time for the benchmark scenario, where the atrium length, atrium height, HRR, and ventilation condition are 50 m, 20 m, 3 MW and 20 m^3/s, respectively. Video S1 shows their comparisons for the whole 20-min fire duration. A pixel shaded in darker (lighter) color means a poorer (better) visibility at a location, and the pure black (white) indicates the visibility of 0 m (30 m). Here the default value of 30 m given in FDS is assigned for the best visibility, based on human's sense of sight.

Fig. 7 illustrates that the poor visibility of the column-shape area originating from the fire source due to the smoke can be easily predicted by the AI model. The overall dynamic characteristics of the smoke layer descending from the ceiling to the ground are well learned and predicted by the AI model. More detailed structures, such as the faster-moving boundary layer on the sidewall, is also accurately captured. On the other hand, some secondary structures of the smoke layer are not reproduced. For instance, the predicted boundary in irregular shape separating the areas having high and low visibilities is not as clear as the CFD simulation. Nevertheless, the overall AI prediction is excellent, because the goal of the current study is to explore the AI method in practical fire safety design, instead of exploring the inherent mechanism of the fire dynamics. In particular, the AI method can give an accurate prediction on the transient smoke-layer height and the ASET.

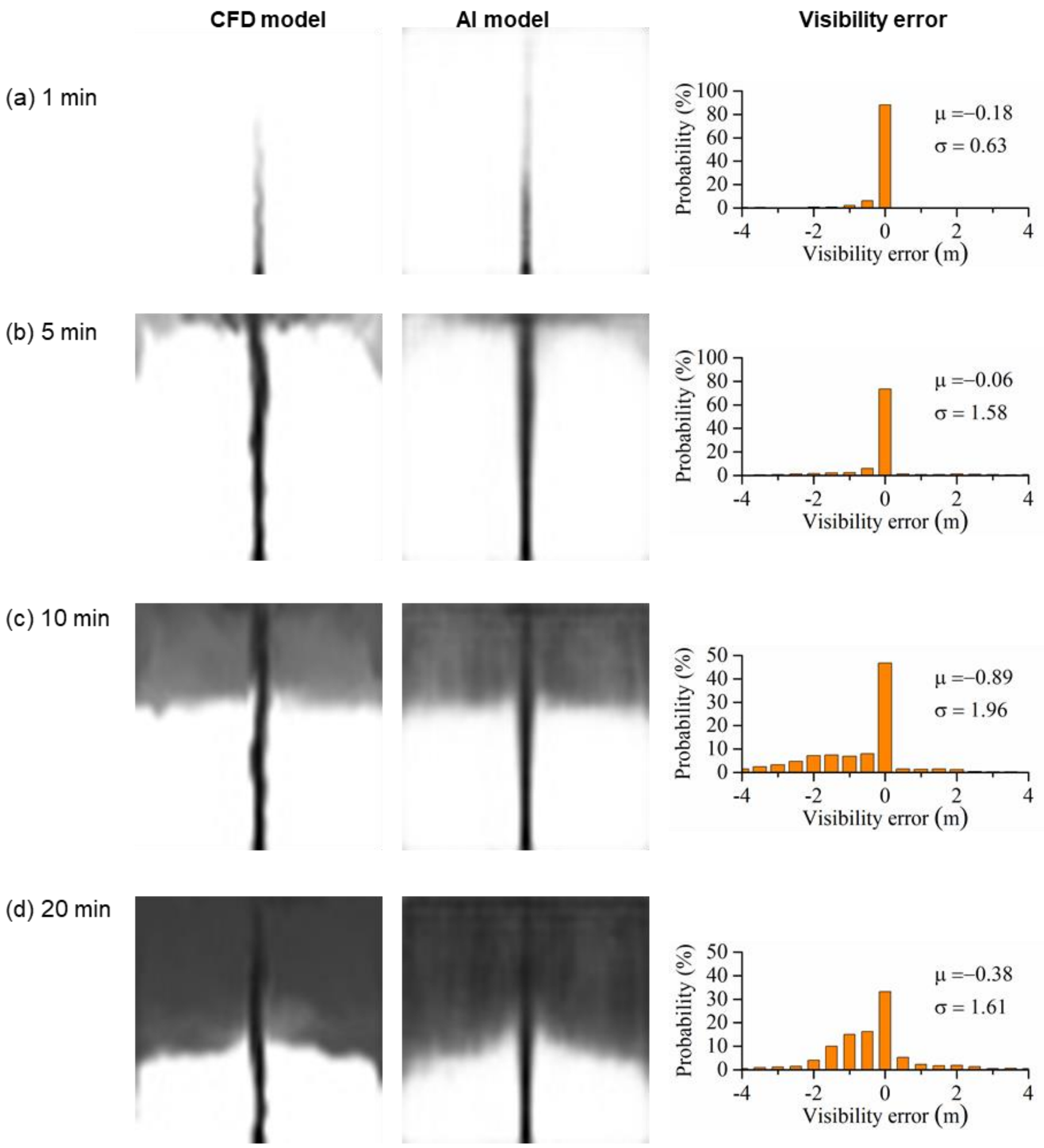

Fig. 7. Actual (left) and predicted (middle) visibility and their difference distribution (right) at various time points: (a) 1 min; (b) 5 min; (c) 10 min and (d) 20 min and Video S1.

To quantify the forecasting quality, the right column of Fig. 7 shows the calculated distribution of the difference between the simulated and forecasted field of visibility. The mean value (μ) and standard deviation (σ) of the visibility difference are roughly within 1.0 m and 2.0 m, respectively. $\mu > 0$ (or $\mu < 0$) means the predicted visibility field is higher (or lower) than the simulated field. The larger σ could be mainly attributed to that the predicted visibility is more evenly distributed while the unsteady flow of the smoke cannot be well predicted. This sophisticated nature of convection and turbulent behavior is difficult for the AI model to learn without prior expertise knowledge.

Fig. 8 further compares the actual and forecasting visibility for the two atrium lengths when atrium height, HRR, and ventilation condition are fixed at 20 m, 3 MW, and 20 m^3/s, respectively. "Appendix A2" gives the comparison between the actual and forecasted visibility under scenarios of various atrium heights, HRRs and ventilation conditions. For all the scenarios, the AI model demonstrates its outstanding performance in predicting the evolvement of smoke visibility.

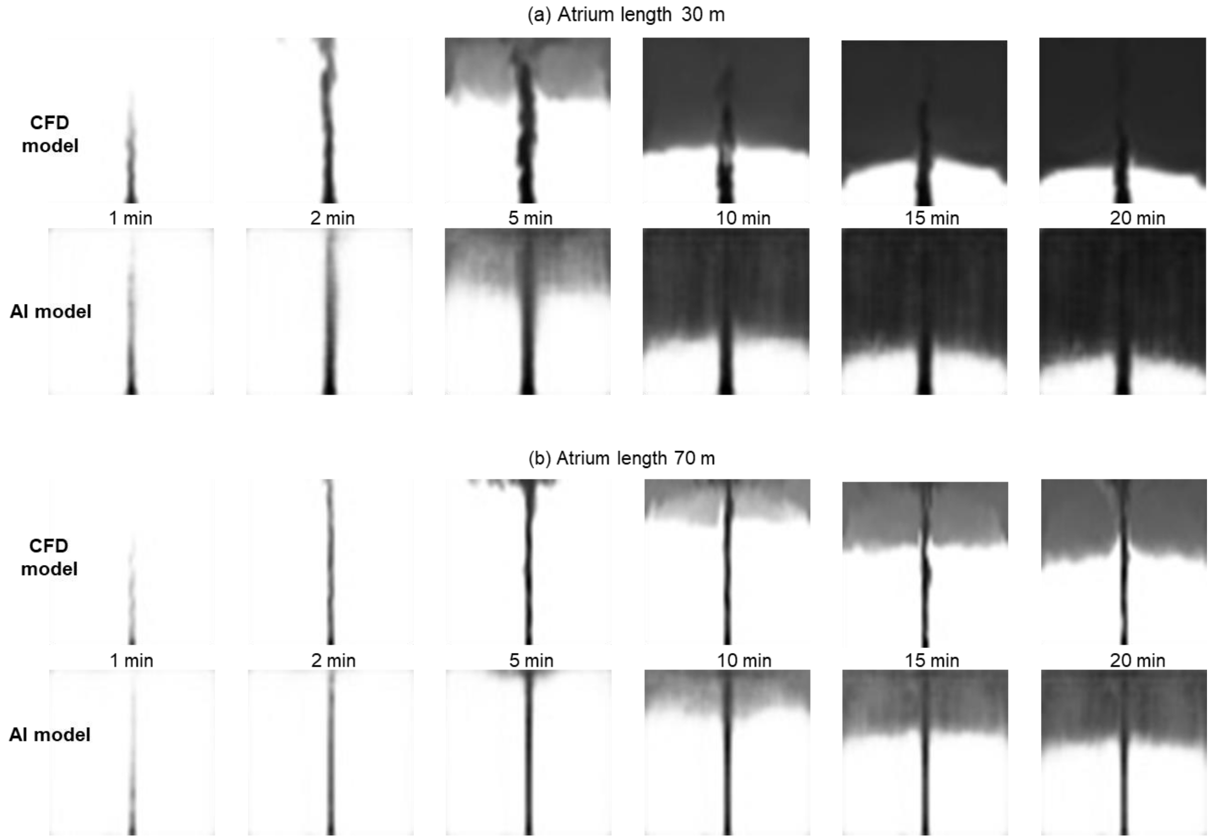

Fig. 8. Comparison of the actual (CFD simulation) and forecasted (AI model) visibility profiles at different moments after the ignition of the fire, where the atrium lengths are: (a) 30 m and (b) 70 m (not to scale).

4.3. Prediction of smoke visibility

The images showing the distribution of smoke visibility is intuitive and informative, while it is difficult to make a quick decision on ASET with these images. In this case, post-processing procedures can be conducted to facilitate the commands on emergency firefighting actions. Observations on the image sequences in Fig. 8 show that the area filling with smoke in low visibility expands from the top to the bottom of the atrium, and the bottom boundary of this area almost remains a moving horizontal plane. According to the recommended fire safety design criteria of the atrium in Hong Kong [14,16], the height of the 10-m visibility should be at least 2.0 m above the ground for 20 min to ensure a safe evacuation. The height where the visibility is 10 m can be calculated from the images. The central 1/3 area of the atrium is excluded to eliminate the influence of the rising fire plume in the calculation.

Fig. 9 compares the 10-m visibility height obtained by CFD simulation and AI Model, which shows the influences of different building and fire parameters. For a clear comparison, selected visibility profiles are shown. In each curve, the initial height before the fire is the atrium height, because it takes some time for the smoke plume to reach the ceiling and form a smoke layer. After 5-10 min, this visibility height drops rapidly since the smoke exhaust capacity has been reached, and the smoke began to fill in the enclosure. After then, for cases with large fire HRR and low atrium height and ventilation, the height drops to a critically low value (see Fig. 9c-d), the descending speed of the smoke slows down when it gets closer to the floor because of the cooling effect and the additional smoke ventilation through the lower opening (windows and the doors with a height of 2 m). The overall coincidence of the calculated curves from the predicted and simulated results once again proves the capacity of the AI method in forecasting the fire-induced visibility evolvement inside an atrium.

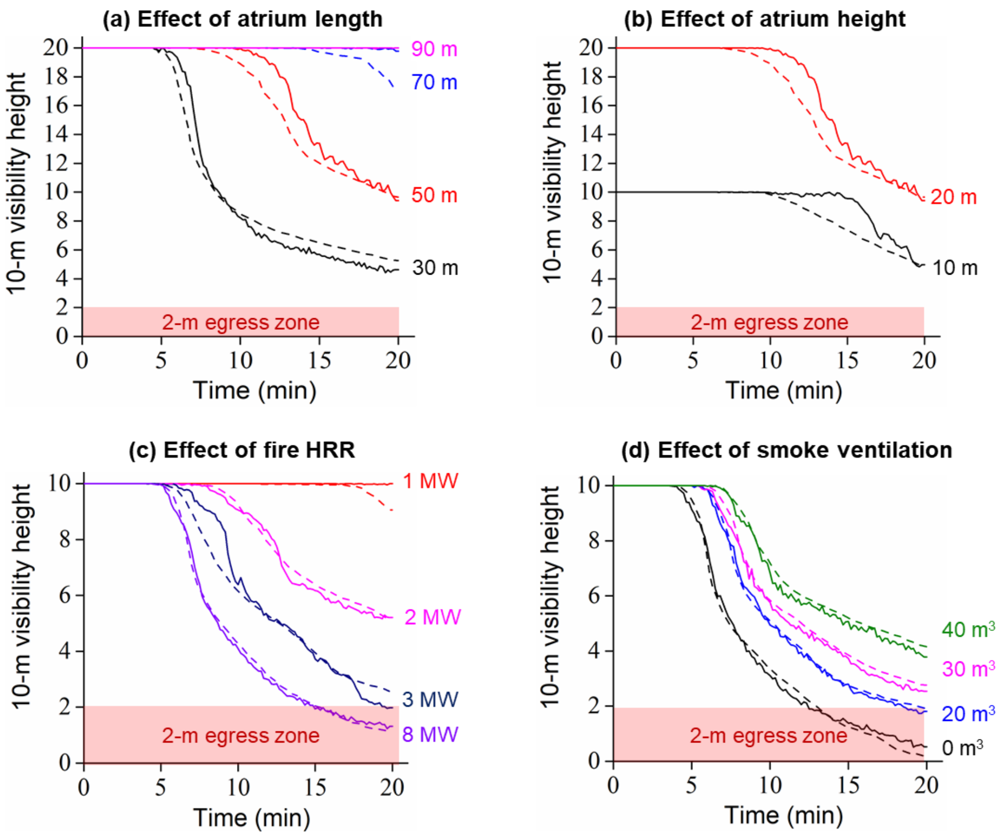

Fig. 9. Height for 10-m visibility vs. time showing the effects of (a) atrium length, (b) atrium height, (c) fire HRR (25,000 m^3, 10 m^3/s), and (d) ventilation condition (25,000 m^3, 8 MW, 10 m^3/s), where solid line is CFD simulation and dashed line is AI prediction.

4.4. *Evaluation of ASET*

Practical performance-based fire safety design concerns more about the relative magnitude of ASET and RSET rather than the detailed information of the evolvement of visibility and smoke-layer heights. The design would pass (fail) if the ASET is smaller (larger) than RSET. Since the RSET is a specified value of 20 min, the judgment of the fire safety design only depends on the accurate prediction of the ASET. The design would pass (fail) when the visibility height is higher (lower) than the specified 2.0 m at 20 min after ignition of the fire. Thus, as long as the visibility situations are still quite good at 20 min (or ASET > 20 min), and specific values of large ASETs are unnecessary unless RSET changes.

Fig. 10 compares the 10-m visibility height at 20 min calculated from the CFD simulation and predicted by the Al model. Ideally, all the data points would locate at the diagonal line if the results can be perfectly predicted by the AI model. The blue (red) points represent cases pass (fail) the requirements of performance-based fire safety design. The coefficient of determination R^2 is calculated as 98.3%, indicating the excellent performance of the proposed AI-method on the prediction of the smoke visibility height and the ASET. Note that the deviation of AI prediction for cases having a higher value of visibility (smoke) height while not affecting the judgment of ASET and RSET, because these cases are fire safe (ASET >> 20 min), which definitely can pass the design requirement.

More attention should be paid to the data points where the critical visibility height is lower than 2 m in CFD simulation, while it is higher than 2 m in AI prediction, that is, a false fire safety. However, such cases are rare and can be avoided by setting a reasonable safety margin. Moreover, the critical visibility height, as well as its evolvement with time, can also be predicted directly using suitable AI methods, such as the typical artificial neural network (ANN) and long short-term memory (LSTM) model adopted in our previous works [37,38]. While in this study, we obtain the information of visibility height by post-processing the predicted images of the 2D visibility contour. One advantage of the proposed method is its convenient adjusting and good generalization. The specifications in codes are not introduced in the AI training, meaning that re-training the AI model is not required if the post-processing code or the requirement of RSET and visibility is revised afterward.

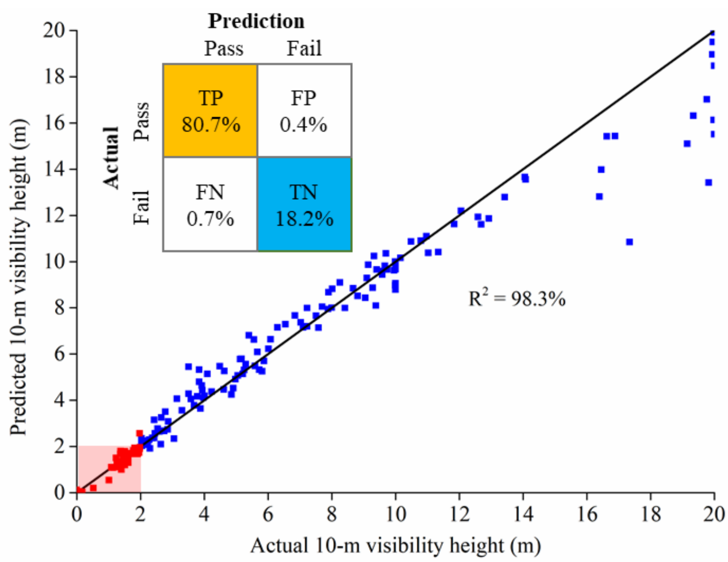

Fig. 10. Comparison of the predicted and simulated 10 m-visibility height at 20 min, where blue (red) points represent cases pass (fail) the PBD requirements of ASET.

Based on the prediction of 10 m-visibility height, the judgment on whether a fire safety design of an atrium pass or fail the specification in codes can be made by the established AI model. The performance of the AI model on the judgment can be evaluated by a confusion matrix [67,68] shown in Fig. 10, the four cells of the matrix represent

- True positive (TP), cases "Pass" are correctly identified as "Pass";
- False positive (FP), cases "Pass" are wrongly identified as "Fail";
- False negative (FN), cases "Fail" are wrongly identified as "Pass"; and
- True negative (TN), cases "Fail" are correctly identified as "Fail".

For the 280 cases considered in this study, almost all (98.9% = 80.7% + 18.2%) the cases are correctly forecasted. Only three cases are wrongly identified are those having 10-m visibility heights quite near the limit of 2 m.

5. Demonstration: Human vs. AI

5.1. A Round Robin of conventional PBD by human professionals

In this work, we invited six volunteer participants who have different levels of knowledge and experience from different fire engineering companies or research institutes. Similar round-robin approach and group efforts were adopted in simulating the Dalmarnock Fire Test One [69–71], warehouse and theatre [72]. Each participant is asked to evaluate the ASET of two atrium cases, as if it is a normal consultancy task or research project. All participants have some fundamental knowledge of fire dynamics and some experiences in conducting CFD fire modeling for PBD.

Input parameters were not specified in the survey form, so participants are recommended to follow their normal practice when conducting ASET/RSET analysis and free to design FDS model based on their project and research experiences. Further amended questionnaire upon participants feedback is given for participants for second round revision. Note that the extent of information (particularly the visibility factor and smoke yield) provided to participants exceeds the typical set of data available for a user when attempting to simulate a fire for the purpose of performance-based fire engineering design. Nevertheless, it is found to be necessary to reduce the large variation in the modeling results. The detailed survey form is provided below.

Participant background

- Professional background: ______________________________
- Affiliation (company/institute): _________________________
- Experience of numerical fire modeling: __________________

Objectives: The aim of this exercise is to understand if experienced fire engineers and scientists can

(1) Judge if ASET last 20 min without doing the numerical simulation of smoke transport, and

(2) Produce similar numerical results of ASET from their independent fire modeling work.

Case specifics: To reduce the randomness in performing the fire model, the simplest cuboid atrium is selected. The fire and structure parameters of the two cases, as well as the makeup air supply [52] and ventilation conditions, are provided in Table 3. This acceptance criterion of AEST in this exercise is defined as **1,200 s** after the ignition of the fire and also considered one specific life safety parameters, i.e., **visibility ≥ 10 m**, which should be satisfied at **2.0 m above the ground level**, based on the PD 7974-6 and the Hong Kong local regulation [15,16].

Table 3. Specifics of structure parameters and fire scenarios.

Category	Parameter	Case 1	Case 2
Structure	Geometry of Atrium, L×L×H (m)	70 × 70 × 20	50 × 50 × 10
	Volume of Atrium (m^3)	98,000	25,000
	Smoke extraction, m^3/s	0 (no ventilation)	10 (mech. ventilation)
	Natural air-inlet from door opening in a pair of wall, w × h (m)	14 × 2	10 × 2
Fire	Fire size (MW)	5 MW	2 MW
	Soot yield (g/g)	0.043	0.043
	Fire growth rate	fast growth	fast growth
	Visibility factor (light-emitting signage)	8	8

Design criteria	ASET (s)	1200	1200
	Visibility at 2 m above ground (m)	10	10
Inquiry (without modeling)	If ASET ≥ 20mins (✓ or ✕)		
	Reason		
Inquiry (with modeling)	If ASET ≥ 20mins (✓ or ✕)		
	CFD code		
	Time spend (h)		
	Feedback		

Note that both selected cases are successful designs (✓), where the evaluated ASET is slightly larger than 20 min (i.e., the RSET), according to the authors' CFD simulation results stated in Section 3. Therefore, it will be challenging for all participants to evaluate the magnitude of ASET and RSET via either intuition or CFD-based numerical simulations.

5.2. *Expert opinion by intuition*

To avoid a stressed environment, all participants could give their "intuition" answers for each case up to 10 min. Some participants used the pen and paper to do a hand calculation, while some just used mental calculation or guessed. Although all participants are considered as experts with years of practice and experience in PBD, their intuition gives very different judgment on the value of ASET, as summarized in Table 4. For Case 1 (98,000 m^3 atrium + 5 MW fire), only Participants B and C thought ASET > 20 min based on their intuition or quick analysis. Participant B thought that the height of the compartment is larger enough for a 5 MW fire in terms of structural fire analysis, so the simulation result should be good. Participant C roughly estimated the smoke filling time expected to be around 3,200 s assuming a smoke production rate of 30 m^3/s for a 5 MW fire.

Nevertheless, the other four participants gave the wrong judgment and believed that Case 1 would fail the fire safety requirement. Participant A believed that the cooling effect for such a large compartment should be important, and the smoke would descend quickly after flow along with the ceiling for 30 m. Thus, Case 1 must fail because of a large floor area. Participant D believed that the enclosure unlikely sustained a tenable condition without smoke ventilation, so Case 1 could not pass the fire safety requirement. Nevertheless, Participant D also commented that reducing the fire growth rate might make ASET exceeding 20 min. Participant E believed the large atrium heigh of 20 m might provide a relatively long ASET to some extent, but the fire HRR was also large, so that ASET > 20 min was not possible.

For Case 2 (25,000 m^3 atrium + 2 MW fire), the participants' quick intuition also gave very different judgments. Nevertheless, unlike Case 1, most participants expressed their large uncertainty and became less confident in their judgment. They commented that the fire size, atrium volume, and provided smoke extraction system were smaller than the cases they met in practice, because in HK, only atrium volume >28,000 m^3 or the ceiling height >15 m needs the PBD.

Participants A and B considered the required air change rate per hour to calculate the required smoke extraction rate. However, they selected different air change rates; that is, A used the value recommended by the HK code, while B used the value from the mainland China code. Participant E examined if the given smoke extraction rate was sufficient by reviewing some empirical equations. Other participants gave their judgment without conducting any mental or hand calculation. As a result, although 4 out of 6 participants gave the correct judgment, most of them were not very sure about their judgment and took a long time to decide. Several participants later confessed that their guess was random in nature.

Table 4. Comparison of participants' judgments on ASET vs. RSET for atrium fire by human intuition, CFD simulation, and AI method, where * means the confidence of judgment is low.

Participant	Background	Case 1 If ASET ≥ RSET = 20 min		Case 2 If ASET ≥ RSET = 20 min	
		Intuition (✓ or ✕)	CFD simulation (✓ or ✕)	Intuition (✓ or ✕)	CFD simulation (✓ or ✕)
A	Fire engineer with 4-years PBD and fire-modeling experiences	✕	✓	✕	✓
B	Fire scientist who used to be a professional fire engineer	✓	✕	✓*	✕
C	Senior fire engineer with rich PBD and fire-model experiences	✓	✓	✕*	✓
D	Junior fire engineer with some fire-modeling experiences	✕	✕	✓*	✓
E	Fire engineer with 2-years PBD and fire-modeling experiences	✕	✓	✓*	✕
F	Fire scientist with rich experience in different CFD codes	✕	✕	✓	✓
Authors	A group of professional engineers and fire science researchers	-	✓	-	✓
AI	-	✓		✓	

✓ means the successful design **ASET ≥ RSET = 20 min**; ✕ means the failed design **ASET < RSET = 20 min**

5.3. Expert opinion by CFD simulation

After the initial judgment by the expert intuition, all participants conducted CFD-based simulation and submitted their own simulation results and judgments. The spent time ranged from several hours to a few days. Their judgments are also summarized and compared in Table 4. The input files for the CFD code were also collected for further analysis, as summarized in Table 5. Except that Participant F used the ANSYS Fluent, all other participants used FDS to conduct CFD simulations. Feedback regarding the level of instruction to be given to participants were discussed, in order to see engineering's selection and judgment for each fire scenario.

Similar to other round-robin fire modelling survey [69–71], different participants have their habits to form the fire model and conduct simulation, although the description of structure and fire is already in good detail. For example, Participants B, D, and E used the mesh size varied from 0.2 to 1.6 for different zones, where smaller mesh size was set around fire location, and the coarser mesh was used for spaces other than fire. On the other hand, Participant A and C, as well as authors, used a unified mesh size, but the selection of mesh size varies from 0.25 and 1.0. None of these six participants conducted a sensitivity analysis for the mesh size, because they all believed their selection was reasonable based on their years of practice.

Table 5. Selected input parameter in Case 2 for different participants.

Participant	HRRUA (kW/m^2)	Fire area (m)	Grid size (m)	Mesh No.	Cell No.	Vent rate (m^3/s)	Vent No.	single vent size (m × m)
A	500	2 × 2	0.25	28	1,799,490	2.5	4	3.5 × 2.75
B	250	4 × 2	0.2/0.4/0.8/1.6	8	400,064	10	1	1.6 × 1.6
C	1000	2 × 1	1	1	200,000	0.5	20	1 × 1
D	500	2 × 2	0.2/0.4	5	806,589	10	1	2 × 2
E	500	2 × 2	0.25/0.5	16	792,352	5	2	1 × 1
F	1389	1.2 × 1.2	0.4	1	390,625	10	1	2 × 2
Authors	500	2 × 2	0.4	3	390,625	10	1	1.5 × 1.5

The selected heat release rate per unit area (HRRPUA) varied from 250 to 1250 kW/m^2 among participants, but the influence should be negligible for the large atrium. The location of the natural makeup opening was also specified to reduce the variance. The smoke extraction was not specified in the survey form. Thus, participants set different numbers of smoke extraction points (1, 2, 4, and 20) and smoke extraction rates per grille (10, 5, 2.5, and 0.5 m^3/s). Also, Participants D and E had specified the start time of smoke extract by either the time of activation of smoke detector setting nearby the fire or the control open after 60 s of fire start, which are standard practices in their daily consulting cases. One thing to notice is that Participant D turned off the radiation solver and set a radiative fraction of 0.35 for fire, while all others turned on the radiation solver.

The prediction results were aligned with the corresponding simulation results. Specifically, if the smoke layer descended below 2 m above the ground, the design was failed (×). However, the simulation results for all participants were far away from consistency, although some of the input parameter settings were essentially the same as others, and no one made any clear mistake. It could be argued that these small differences in predicted ASET are reasonable and caused by human nature, but the outcomes of design (success/failure) and approval (pass/no pass) could be completely opposite. This is partially because the actual design is near the evaluation criterion. More importantly, every engineer has their own interpretation on the fire scenarios and modelling habits, which inevitably cause differences.

On the other hand, although FDS and other CFD tools are recognized tools for simulating smoke movement and designing the fire engineering strategy, these tools required extensive knowledge and understanding of the rationale behind input parameters to avoid manipulating the results. Nevertheless, even for experienced professional fire engineers, it is challenging to get consistent modeling results and convince each other, as well as the AHJ.

In contrast, the AI-based PBD has a great potential to avoid the laborious and costly process of CFD simulation and years of training of CFD modelers in convectional fire engineering PBD. Once trained by the big database of massive numerical fire simulations, the AI model can give quick and accurate predictions in a matter of seconds or minutes, and the results are consistent without any human tunning and manipulating. It can also help AHJ to quickly review PBD cases. More detailed results of the two cases predicted by the AI model are illustrated in Fig. A3. Although the construction of the database and the training of the AI model will take years, as the database and case number grow, the AI model could act as a large group of experienced professional fire engineers to provide a more reliable design. As the development of conventional PBD takes several decades, years of research and development are also needed before the AI-based PBD can be applied and accepted by the community.

6. Conclusions

This study proposed a smart framework for fire engineering performance-based design (PBD) to predict the smoke motion and ASET in atrium fire by AI model. A numerical database of 280 cases, covering different atrium dimensions, fire HRRs, and ventilation conditions, was established for training the TCNN model. Results demonstrated that the proposed AI model could predict the evolution of the visibility (or smoke-layer) profile in the large enclosure, thus determining the ASET in the given design of atrium and fire. As a reference, six participants with a good knowledge of fire dynamics and modeling are invited to conduct case studies with both their intuition and the PBD with CFD tools as a regular consultancy task. Compared to conventional CFD-based PBD by professional fire engineers, AI method provides more consistent and reliable results in a much shorter time.

This research verified the feasibility of using AI in fire-engineering PBD, which may reduce the time and cost in creating a fire-safety built environment. A better performance of the AI model could be achieved if the number of the layers and units in each layer are tunned, and if more fire scenarios (e.g., fire location, fire spread, and soot yield) and building parameters (e.g., shape and layout) are simulated to form a larger database. More importantly, the AI model is preferably to be verified by real- or large-scale atrium fire tests once the target building is constructed. The future work should focus on these potential research areas to improve the smart fire engineering design.

CRediT authorship contribution statement

Ling-chu Su: Investigation, Writing - original draft, Formal analysis. **Xiqiang Wu:** Writing - original draft, Investigation, Methodology, Formal analysis. **Xiaoning Zhang:** Investigation, Resources, Formal analysis. **Xinyan Huang:** Conceptualization, Methodology, Supervision, Writing - review & editing, Funding acquisition.

Declaration of Competing Interest

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

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Appendix

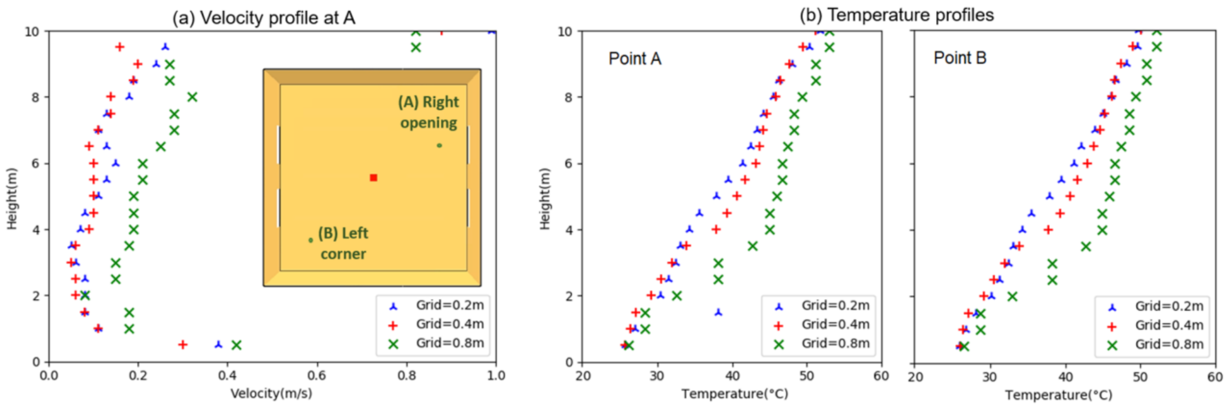

Fig. A1. The grid sensitivity analysis for the CFD modeling of an atrium fire, (a) velocity profile, and (b-c) temperature profiles at two random locations, where the atrium dimension is 30 × 30 × 10 m^3, and the fire HRR is 1 MW.

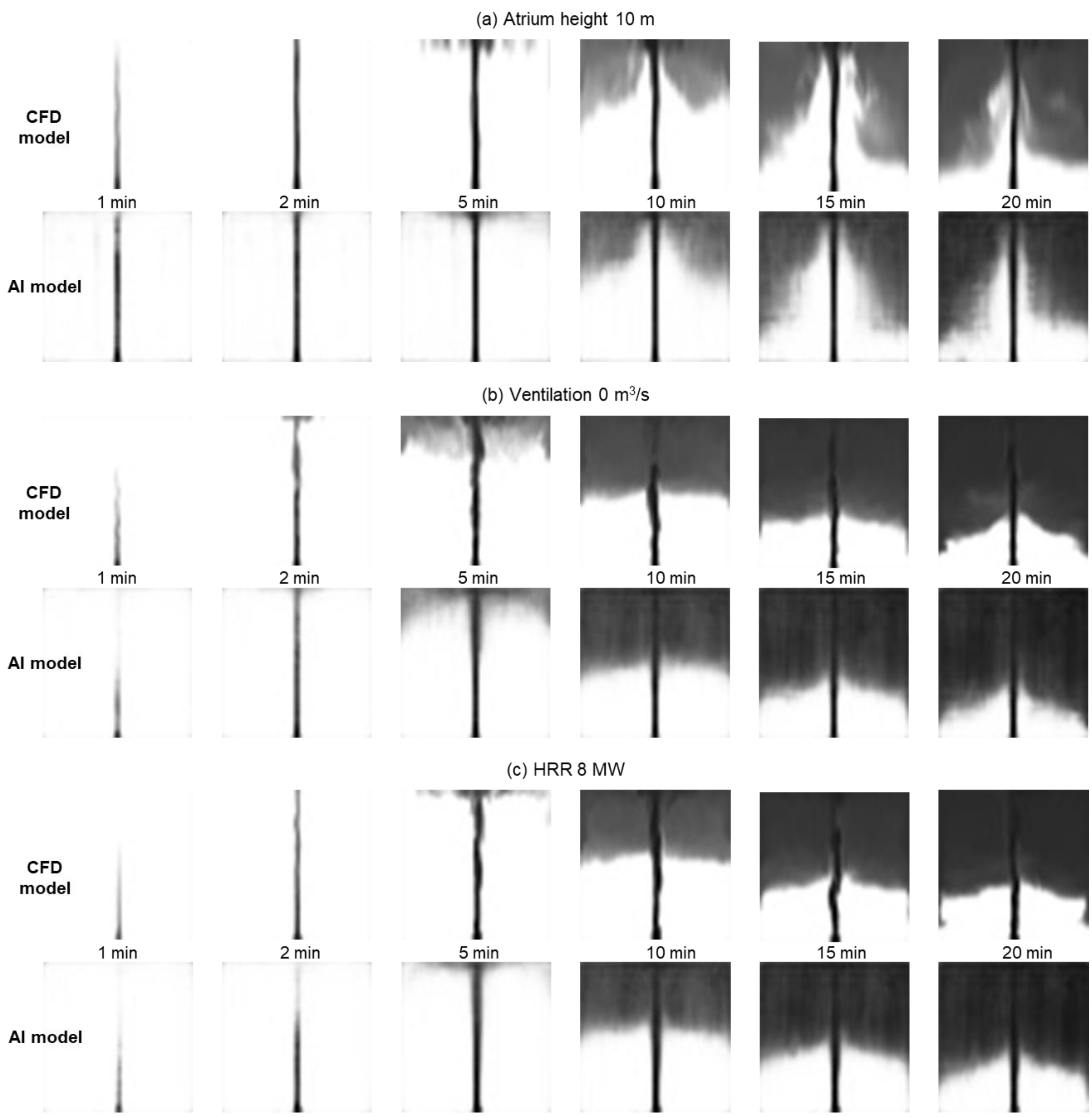

Fig. A2. Comparison of the actual (CFD simulation) and forecasted (AI model) visibility profiles at different moments after the ignition of the fire, where (a) atrium height is 10 m; (b) ventilation is 0 m^3/s and (c) HRR is 8 MW, differed from benchmark case.

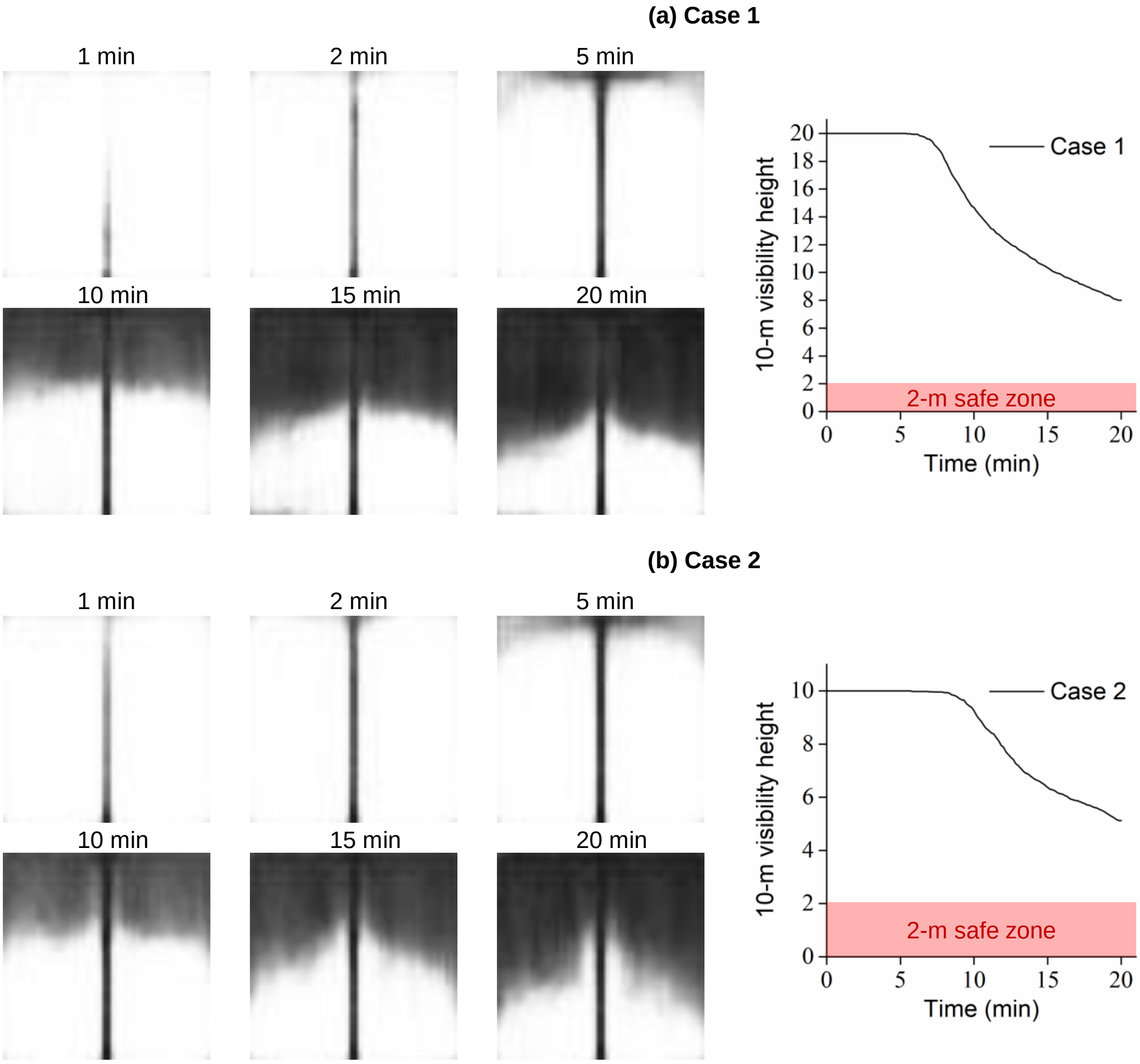

Fig. A3. Predicted visibility profiles at different moments after fire ignition for: (a) Case 1 and (b) Case 2.