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Artificial Intelligence tool for fire safety design (IFETool): Demonstration in large open spaces

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ABSTRACT

Fire modelling is a common practice in building fire safety analysis, but it is costly. This work develops an AI software, Intelligent Fire Engineering Tool (IFETool), to speed up the fire safety analysis and quickly identify design limits. A big numerical atrium-fire database is firstly formed by considering key building and fire parameters. Then, a deep learning model is trained to predict the evolution of tenable smoke visibility, temperature and CO concentration with an accuracy of 97%. The tenability descending profile is further processed to assess the available safe egress time (ASET) and the fire safety of the atriums that have complex roof shapes and slab extensions. This AI design software is able to make a quick assessment of the proposed atrium fire engineering design and give valuable suggestions for potential improvement. Finally, the operation guidelines of IFETool are provided for common design tasks of atrium fire safety.

Abbreviations

AI	artificial intelligence
AHJ	authority having jurisdiction
ASET	available safe egress time
CFD	computational fluid dynamics
CNN	convolutional neural network
FDS	fire dynamics simulator
HRR	heat release rate
IFETool	Intelligent Fire Engineering Tool
IoT	Internet of Things
MSE	mean squared error
PBD	performance-based design

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RSET	required safe egress time
SER	smoke extraction rate
TCNN	transposed convolutional neural network

1. Introduction

The prescriptive building fire safety design approach by adopting regulations and codes has been traditionally adopted around the world [1–3]. They are implemented conveniently by setting minimum safety requirements and provisions, so they are flexible to satisfy the requirements of users, including architects, consultants, and clients. Although these codes could be reviewed and amended regularly, it is intuitively defined in nature, and major improvements often occur only after significant fire incidents.

Today, the iteration of innovative architectural design concepts and construction materials is extremely fast to satisfy the development of urbanization and the demand for mega-cities [2]. More holistic fire strategies are preferred in practical fire safety design, putting the buildings at risk under fire. Therefore, the performance-based design (PBD) method, built on an engineering basis, has gained wider popularity over the last few decades [4]. Moreover, PBD adopts the latest scientific understanding of the fire-smoke dynamics and human behaviors in fire. Compared with the prescriptive approach, PBD can be conducted with special design objectives, such as sustainable design goals, smart city, and the most cost-effective solution set by stakeholders.

1.1. PBD approaches and challenges

The emergence of PBD in building fire engineering is driven by a scientific understanding of fire phenomenons and the fast development of computational engineering tools, especially computer-aided design (CAD), zone models, computational fluid dynamics (CFD), and pedestrian modelling software (Fig. 1). These tools incorporate empirical correlations (e.g. design fires [5,6]) to describe fire behaviours or predict fire and smoke flow by numerically solving the conservation equations, including the Fire Protection Engineering Tool (FPETool) [7], Consolidated Model of Fire and Smoke Transport (CFAST) [8], Fire Dynamics Simulator (FDS) [9], FireFoam [10], AtriumCalc [11], and Pathfinder [12], while most of them have been developed since the early 1990s. These tools have been verified and validated by numerous studies. For example, a series of full-scale experiments were done to validate the CFD modelling of building and tunnel fires [13–21], in which a good agreement between experimental and simulation measurements was observed, especially in the far field of the plume.

Currently, these tools are widely acknowledged by the industry as a benchmark during the building design stage and applied by fire engineers to evaluate the capability of the smoke control system, the response of fire protection systems, the path of human evacuation, and the fire safety level of designs. However, there are several problems in applying these computational tools in fire engineering PBD.

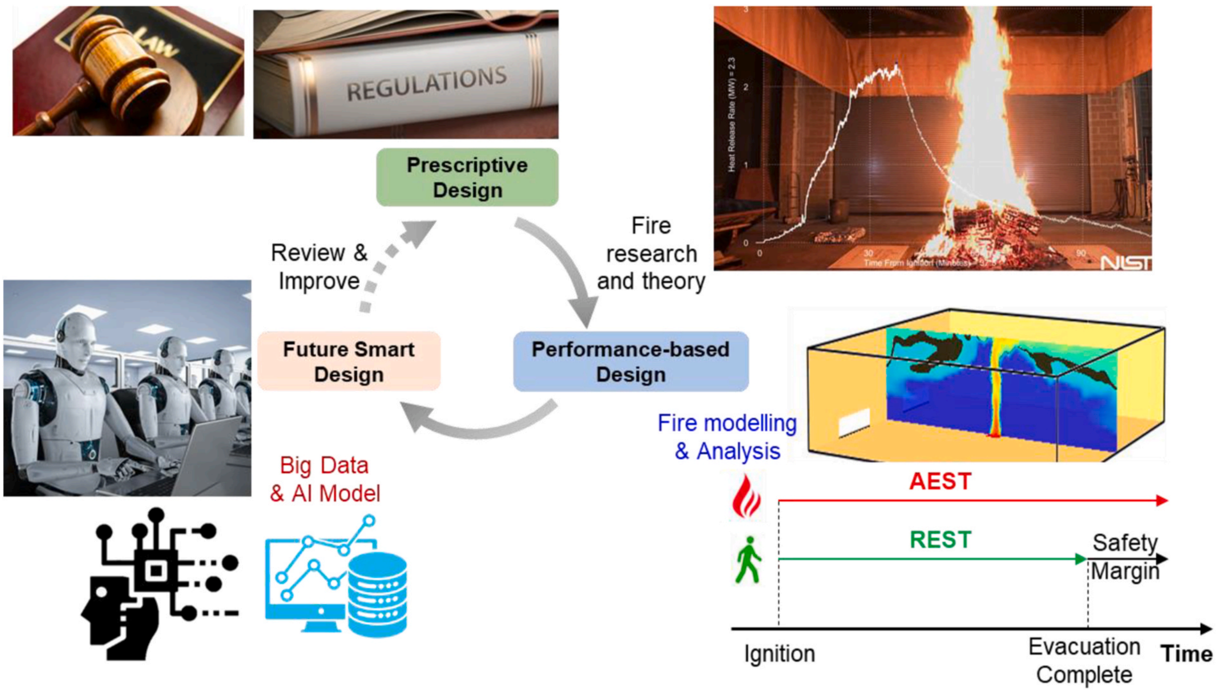

Fig. 1. The evolution of fire engineering design from conventional prescriptive codes to a performance-based approach to the AI-based smart design.

- Fire is an extremely complex phenomenon and to simulate a fire event, there are many inputs and sub-models required to be set in fire modelling software. The inappropriate model set-ups are commonly seen, and it requires great efforts of peer review from both internal and external.
- PBD design, especially with CFD fire modelling, is costly due to the demand for considerable computational resources and the requirement for long-term training and working experiences, which are difficult to summarize and learn by junior designers.
- Design limits cannot be fully explored. Only limited fire scenarios are simulated due to the high computational cost. Most computational works are essentially repeated and tedious routines.
- The validity of fire models and the reliability of simulation results are often doubted by the Authorities Having Jurisdictions (AHJ). Nevertheless, it is time-consuming and difficult for AHJ to point out a specific design issue, even after being provided with the source code.

Nowadays, with the gradual forming of design regulations or paradigms for specific infrastructures, e.g., airport and underground infrastructures [22], fire engineering PDB has become an expensive type of prescribed design [23]. These issues hinder merits and credibility of PBD for practical fire safety design.

1.2. AI-assisted fire design

The recent developments of Artificial Intelligence (AI), especially the deep learning algorithm, have shown its potential in reshaping building fire safety design [3,24], structure fire resistance [25–28], and fire detection and firefighting activities [28–32]. In particular, machine learning methods were applied to predict the fire processes, which is comparable to the results of CFD simulation at both steady [33,34] and transient stages [3,35]. In addition, combing with the Internet of Things (IoT) system, AI models can not only identify the location and severity of fire [32,36] but also forecast fire developments [35,37] and fire evacuation [38–40], and structure fire resilience [25–28], giving early warnings of critical fire events to support smart firefighting. It is noteworthy that these AI-driven fire forecasts can be achieved in real-time, which is extremely difficult, if not impossible, for traditional CFD fire simulations.

Recently, machine-learning design and auditing tools have been developed to assist the compliance checking of architectural CAD drawing with the prescriptive regulations [24,39,41–44]. However, without costly numerical simulations, it is still challenging to reveal the hidden correlations between the design parameters of building and fire (i.e., inputs) and fire evolutions and untenable situations (i.e., outputs) [45,46]. Our latest work [3] has demonstrated the feasibility of adopting a deep-learning algorithm and

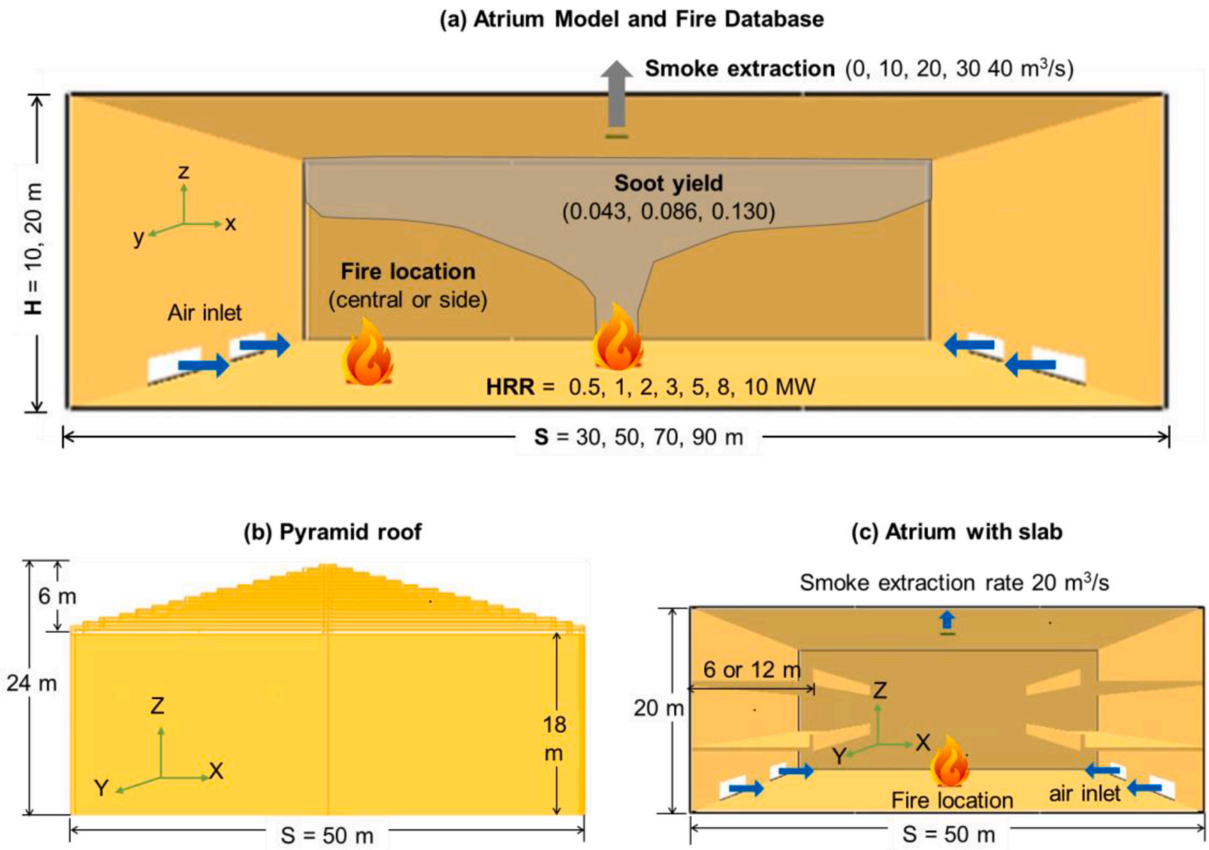

Fig. 2. Numerical model and critical parameters of atrium fire, (a) simplified atrium with different fire scenarios, (b) atrium with a pyramid roof; and (c) slab extensions having a width of 6 m or 12 m.

pre-established CFD fire database to predict smoke motion inside a simple atrium and estimate the Available Safe Egress Time (ASET) within a few seconds. These neural-network-based correlations can provide preliminary assessments for fire engineers to reduce the number of fire simulations required to understand the fire safety performance, judge the validity of simulation results, and improve working efficiency. Moreover, the AI tool can also assist AHJ in quickly evaluating the reliability of PBD, reviewing the CFD fire simulations, and spotting problems. Eventually, the AI tool could help upgrade the current fire codes to improve building fire safety in a more cost-effective way (Fig. 1).

This paper aims to extend our previous work [3] by encoding an upgraded AI model into an Intelligent Fire Engineering Tool (IFETool) software to facilitate fire engineering PBD. The IFETool incorporates a pre-trained deep-learning AI engine trained by a big database of CFD fire simulations of various fire scenarios. The accuracy and efficiency of the IFETool are demonstrated via the fire-safety PBD of different atriums, and the methods and procedures of using this software are presented in typical design cases of consulting practices.

2. AI model construction

2.1. CFD simulation

The CFD-based fire model is a widely used analysis tool for predicting fire growth and smoke movement in the PBD of building fire safety. Often, these simulations use the Fire Dynamic Simulator (FDS) developed by NIST [47]. Following the previous work [3], simplified large atriums are used for demonstration. Several key parameters of atrium fire safety [48–52] are chosen and varied (Fig. 2a).

- **Fire size.** The fire size or heat release rate (HRR) in the atrium, which significantly affects the total smoke generation, may vary according to practical experiences and experiments [48–52]. Seven different values of peak HRR (0.5, 1, 2, 3, 5, 8, and 10 MW) were considered with the same HRRPUA of 0.5 MW/m^2. Conservatively, the t^2 fire with a fast fire growth rate of 0.0469 kW/s^2 was used for each case until reaching the peak value of fire HRR.
- **Fire location.** The fire location affects the fire plume and smoke motion [53,54]. Two locations of the fire source were simulated, where the fire was placed in the center or near the sidewall.
- **Fire soot yield.** The smoke soot yield depends on the type of combustible material. Various types of materials could be burning in a real fire, so that three soot yields were selected, i.e., 0.043, 0.086, and 0.130 g/g [55], to cover different fire scenarios.
- **Building geometry.** The geometry of the building in practice could be very complicated. A simplified geometry with a box shape is assumed for the atriums when establishing the training database. The floor was square with an edge length ranging from 30 m to 90 m. The established fire model has included the atrium volume ranging from 9000 m^3 to 162,000 m^3. Two atrium heights, 10 m and 20 m, were considered in the simulations.
- **Smoke extraction rate (SER).** The capacity of the SER influences the visibility inside the atrium and the tenable conditions. If the atrium volume is large, the smoke influence area could be tenable without providing a smoke control system (SER = 0), but the AHJ may still suspect a high fire risk, regardless of good results demonstrated in numerical modelling. Five smoke extraction rates (0, 10, 20, 30, and 40 m^3/s) were investigated to suit different design purposes.

A total number of 1080 fire scenarios were simulated to form a training database (see Table 1). In all the simulations, the ambient temperature was set as 25 °C. The fuel was a mixture of natural materials and plastic compounds in equal proportions. Vents with corresponding volume extraction rates were defined to represent the mechanical smoke extraction systems in practice. The make-up inlet air is another influential parameter for the atrium fire smoke ventilation design [17,20,56]. In this study, natural air make-up was provided through the four entrances at the bottom level, as it is a common engineering practice. The width of each door is one-fifth of the atrium length and the height is 2 m. In the further development of the database, different air make-up configurations, e.g., mechanical air make-up, would be included.

Each atrium fire simulation lasted for 1200 s, which was long enough to consider the practical egress time. 2-D slices at the y-plane (vertical profiles) were set for visibility, temperature, and CO concentration, to record the evolvement of tenable conditions inside the atrium. The grid resolution is a crucial setting in FDS to guarantee the accuracy of the results. The grid size can be determined based on the non-dimensional parameter ($D^*/\delta x$) suggested in the FDS user's guide, where D^* is a characteristic fire diameter, and δx is the control volume size [47]. The value of the grid size is smaller for a lower HRR, and it is suggested between 4 and 16 [57]. For a fire of 1 MW, which is rarely used to represent the worst fire scenario in an atrium of 30 m × 30 m × 10 m, the simulated results have no

Table 1
Parameters varied in the fire model (1080 cases in total).

Parameters	Range
Fire location	"central" and "side"
Soot yield (g/g)	0.043, 0.086, 0.130
Design fire size (MW)	0.5, 1, 2[b], 3, 5, 8[b], 10
Atrium length[a] (m)	30, 50, 70, 90
Atrium height (m)	10, 20
Smoke extraction rate (SER) (m^3/s)	0, 10, 20, 30[b], 40

[a] The atrium cross-section is square.
[b] Parameters only apply for cases with 0.043 g/g soot yield and fire in the center.

significant difference when reducing the grid size from 0.4 m to 0.2 m, according to our previous grid sensitivity analysis [3]. Thus, the grid size of 0.4 m was applied for the simulations of all the fire scenarios to speed up the simulation process while maintaining accuracy. This same grid size also facilitates the postprocessing of the simulation result to form the training database. The total number of cells was between 140,625 and 2,531,250 for atrium volumes ranging between 9000 m^3 and 162,000 m^3. The default thermal boundary was set to all wall surfaces. The simulations were run on a 32-core server. The simulation time varied from 12 h to 24 h for a single case, depending on the atrium size.

2.2. Database generation and model training

After simulation, the simulation results and fire scenario parameters are used to form a big database (Fig. 3a) for AI model training. Building and fire design parameters, consisting of the atrium length and height, fire location, size and soot yield, smoke extraction rate, and post-ignition time (or burning duration), were used as the model input in sequence. In total, there are 1080 scenarios as listed in Table 1. The post-ignition time at an interval of 10 s was also considered input since the tenability profile varies during the 1200 s simulation time. The total number of data samples for each criterion is then 1080 scenarios times 120 post-ignition times, which is 129,600. Series of tenability profile records, including visibility, temperature, and CO concentration, at the y-plane for every 10 were extracted from Smokeview using an in-house middleware "fds2ascii", which served as the target of the model output. To convert the results into a unified format for subsequent training and result display, the tenability images are linearly scaled into 50 × 50 pixels. Then, all the labelled samples were randomly grouped into a training dataset, a validation dataset, and a testing dataset with a ratio of 60%, 20%, and 20%, respectively. The training dataset is used to learn this sample of data and capture the hidden correlations between design parameters and tenability outputs. The validation dataset is used to evaluate the model during the training process which provides us guidance to fine-tune the model hyperparameters. The testing dataset is used to quantify the forecast quality once the model is completely trained.

Herein, the visibility result ranges from 0 m to 30 m, while the temperature and CO concentration results are ranged from 25 °C to 1040 °C and 0 ppm to 5646 ppm respectively. Since the result range between these criteria is significantly different, to avoid possible interference during the training, each criterion is trained with its own 129,600 data samples. However, even with data normalization during the training, AI predictions of the temperature and CO concentration are still not promising. The possible reason is that the upper limit of these two criteria is set higher, i.e., 1040 °C and 5646 ppm around the flame, while the lower value regions outside the fire plume become too low to recognize accurately. Therefore, the temperature records were reprocessed with a threshold value of

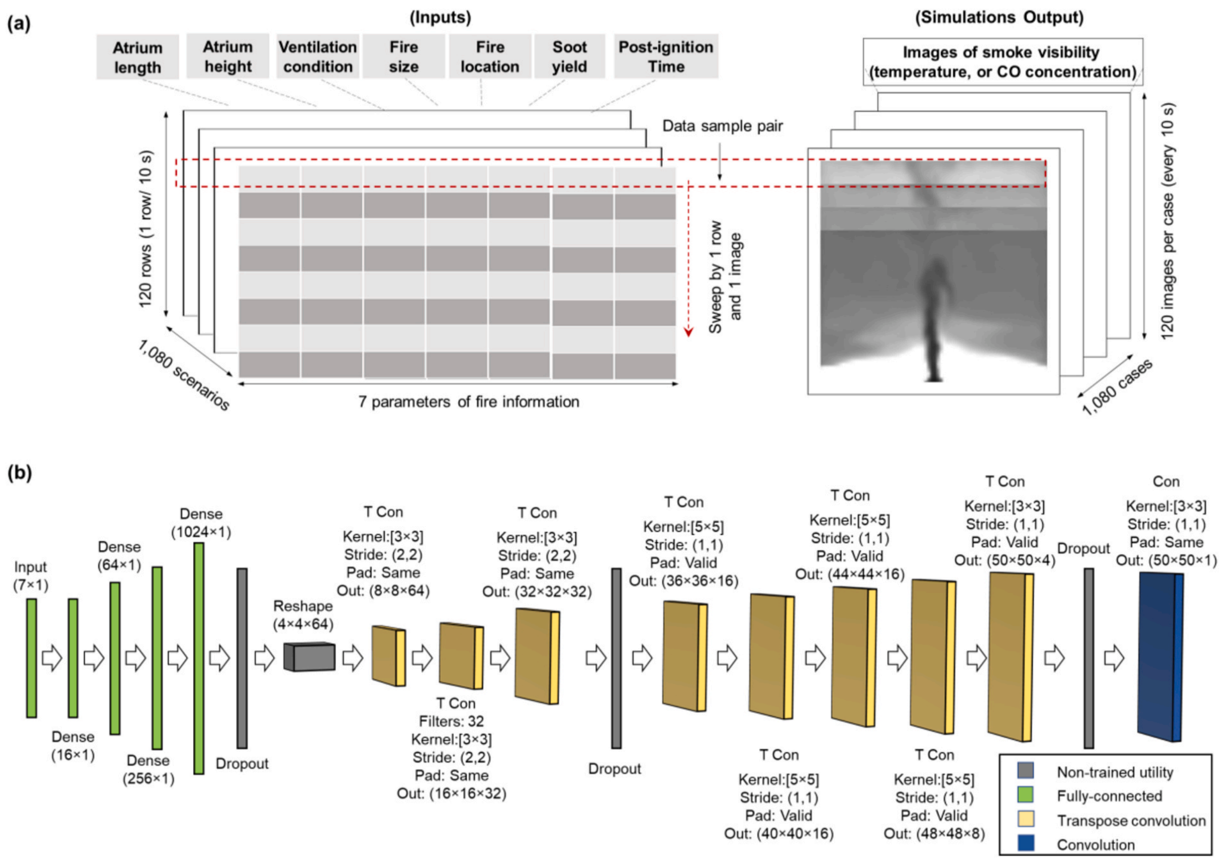

Fig. 3. Construction of the AI model: (a) generation of the training database; and (b) architecture of the proposed TCNN model.

100 °C in order to better identify the 60-°C tenability limit, and a 1000-ppm threshold is set for CO concentration. Then, the distribution of temperature and CO can be better recognized by the AI engine.

Convolutional neural network (CNN) has been widely adopted to capture the spatial and temporal features from images, while transposed convolutional neural network (TCNN) behaves in the opposite way which converts simple input data to higher-dimensional space [58]. The performance of TCNN in predicting fire-induced temperature field and smoke movement has been demonstrated by previous researchers [3,32]. Hence, a deep learning AI model was built up with (TCNN) layers to obtain the images showing the tenability profiles with the given input. The detailed architecture of the AI model (Fig. 3b) was updated from our previous work [3]. The mean squared error (*MSE*), defined as the difference between the CFD simulations and AI predictions, was adopted as the loss function. The coefficient of determination R^2 was adopted to illustrate the accuracy of the prediction. The loss can be minimized through a large number of training iterations. Since the memory on the server to train the AI model is limited, the training samples were grouped in small batches for balancing training efficiency and maintaining stability. The trained model, including network structure and weight of each layer, could be deployed for practical use.

3. IFETool software

3.1. Conceptual design

The Intelligent Fire Engineering Tool (IFETool) is the software incorporating the proposed deep-learning AI engine to assist the building fire engineering designs. Fig. 4a illustrates the conceptual design of this intelligent software. The goal of IFETool is to use AI to predict the tenability descending profile against time and assess whether the proposed fire engineering PBD meets the tenability criteria so that building a comprehensive database having different fire scenarios is the first step. A large number of CFD fire simulations should be conducted for different fire scenarios and buildings (e.g., types, design features, and fire protection systems).

Herein, IFETool version 1.0 only considers the atrium fire, and a big atrium fire database was established, as described in Section 2.2. Then, the database was used for training the developed AI model. Both the quality of the database and the training of the deep learning model play a vital role in the accuracy and performance of IFETool. The size of the database will be further increased by including more fire scenarios and different types of buildings in the future version. To make the IFETool easy to use, the user interface was developed to facilitate the input and visualization of the output results. The inputs of this software are necessary parameters for fire safety design, including building information, fire scenarios, and fire safety criteria. After calculation, the model will give predictive results and display them on the user interface.

3.2. User interface and operation

The current IFETool version 1.0 is open access (http://ifetool.firelabxy.com/). Fig. 4b shows the operation panel of the IFETool, which contains four sections, e.g., input field, output results, tenability profile visualization, and the display of the smoke height curve. After inputting required parameters manually, this AI software can visualize the distribution of selected criteria at a specific moment, display the profile of tenability evolving with time, and determine whether the current fire design meets the PBD criteria, e.g., ASET > required safe egress time (RSET). The input parameters are the design parameters of fire and building, as listed in Table 1.

After filling in all inputs and clicking the button "Calculate," the IFETool will call the pre-trained AI model to predict tenability profiles. The descending smoke height will also be calculated and displayed **within 1 s** (see Fig. 4b). The users should be noted that since the grid size of 0.4 m was applied to the numerical training database, the predicted result subsequently has an uncertainty range of 0.4 m considering the results within a grid is uniform. This uncertainty is caused by the CFD simulation accuracy and could be mitigated by introducing a certain value of safety margin. If the user wants to start a new case, just click "Reset," and all the input and

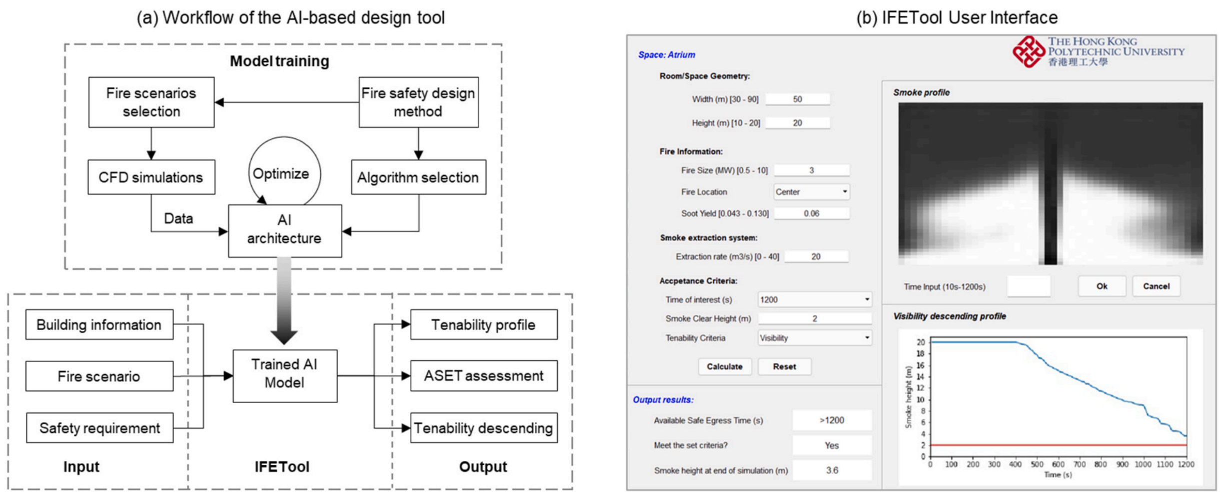

Fig. 4. (a) Conceptual design of Intelligent Fire Engineering Tool (IFETool); and (b) User Interface of the IFETool and the base-case results after inputting parameters and calculation (open-access at http://ifetool.firelabxy.com/).

output will be cleared.

The inputs of each parameter are preferably set within the range listed in Table 1. Specifically, the fire can be chosen at the "Center" or "Side." The value of the atrium length, atrium height, SER, fire size, soot yield, and post-ignition time are better in their corresponding ranges of [30, 90] m, [10,20] m, [0 m^3/s, 40] m^3/s, [0.5, 10] MW, [0.043, 0.130] g/g and [0, 1200] s. Nevertheless, the pattern matching capacity of this AI tool is also powerful enough to provide a rough estimation for the atrium with complex roofs and slab structures that are not included in the training database (discussed in Section 4.2). Additional input parameters will be added when the fire database grows bigger.

Currently, the acceptance criterion of IFETool v1.0 applies to smoke visibility, gas temperature, and CO concentration, which are the typical-used criteria in practical projects. The software can be further upgraded to include other criteria, such as heat flux and air velocity, to meet various design safety objectives. More functions will be available in the menu bar. For instance, the user can export the input information and predict results to a CSV file; a user guide will be provided under the button "Help" to demonstrate how to use the IFETool. This software has been filed for a patent, and it will be continuously maintained and updated. The IFETool aims to provide a prompt result for professional fire engineers, which is similar to the classical FPETool [7] and AtriumCalc [11], an analytical tool to analyze the smoke control system quickly for the atrium and provide initial values for CFD fire modelling. Nevertheless, its accuracy is limited by the accuracy of the CFD simulation database. Thus, users should understand the limitations of the IFETool and interpret its results in a rational way.

4. Validation and performances

4.1. Performance of the AI model

This section assesses the performance of the AI model on the training database. Fig. 5 shows the evolvement of *MSE* loss and the coefficient of determination R^2 during the training process. It shows that the *MSE* approaches a near-constant value of 0.0053 after training for 380 epochs, and the corresponding R^2 converges to 97%. The training accuracy reaches extremely high value around 50 epochs, since the loss is still decreasing and the accuracy is still increasing, the model is totally trained 500 epochs to get its best performance. The high score closing to 100% shows that the performance of the AI model is good enough for resolving the spatially varied smoke visibility.

Fig. 6 further compares the simulated and predicted tenability profiles (cases from the 20% test sets) and checks the capability of the trained AI model in predicting the spatially resolved critical values. Fig. 6a shows the comparison at different moments after ignition for the fire scenario with a 30 × 30 × 10 m^3 atrium with 10 MW HRR of central fire and 0.086 g/g soot yield, and no smoke ventilation (Case 1). A darker pixel indicates a poorer tenability value at this location. The fire plume in cylindrical shape above the fire source with poor safety level can be easily learned and recognized by the AI model. The overall smoke layer descends from the ceiling to the designed smoke clear height can be accurately reproduced. As expected, the fluctuant and turbulent eddies of the smoke are ignored by the AI engine, which has no influence in judging the tenable condition (see a detailed comparison in Video S1).

Fig. 6b illustrates the fire scenario when the smoke ventilation is increased to 20 m^3/s with a larger dimension of 50 × 50 × 20 m^3 (Case 2, Video S2). It can be seen that the tenable conditions (or safe regions) benefit from the extension of the smoke reservoir and smoke extraction, while the CO concentration is affected the most significantly. While the ventilation system is introduced, the air movement within the space is more complicated with strong air entrainment and turbulent vortex structure, especially at the later stage of the simulation when the smoke layer approaches the air inlets. These turbulent boundaries are ignored by the AI because, in the training process, it shows a negligible relevance to the final design criteria. Since the goal of the proposed tool is not to investigate the inherent mechanism of the fire dynamics, the simplification of the unnecessarily detailed vortex structure allows a quicker prediction of the result. Fig. 6c illustrates the fire scenario when the fire is moved from the center to the side and the soot yield is increased to 0.130 g/g (Case 3, Video S3). Although the result becomes more complex than a symmetrical profile, the AI model well predicts its evolution and boundaries.

According to the requirements of acceptance criteria in common practices, at least 10-m visibility, 60-^{o}C temperature, and 1000-ppm CO concentration should be maintained at 2 m above the floor level within 20 min to safeguard the safe egress [59]. Subject to the design team, the smoke clear height may be defined as a higher position to reduce the smoke damage under fire. Conservatively, the

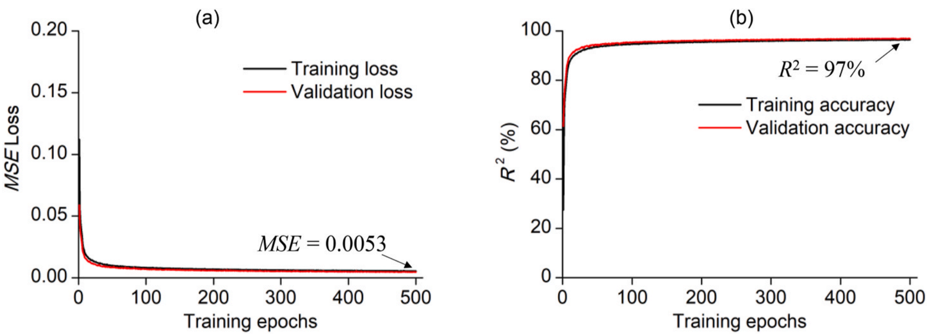

Fig. 5. The evolvements of training and validation (a) loss and (b) R^2 with the training epochs.

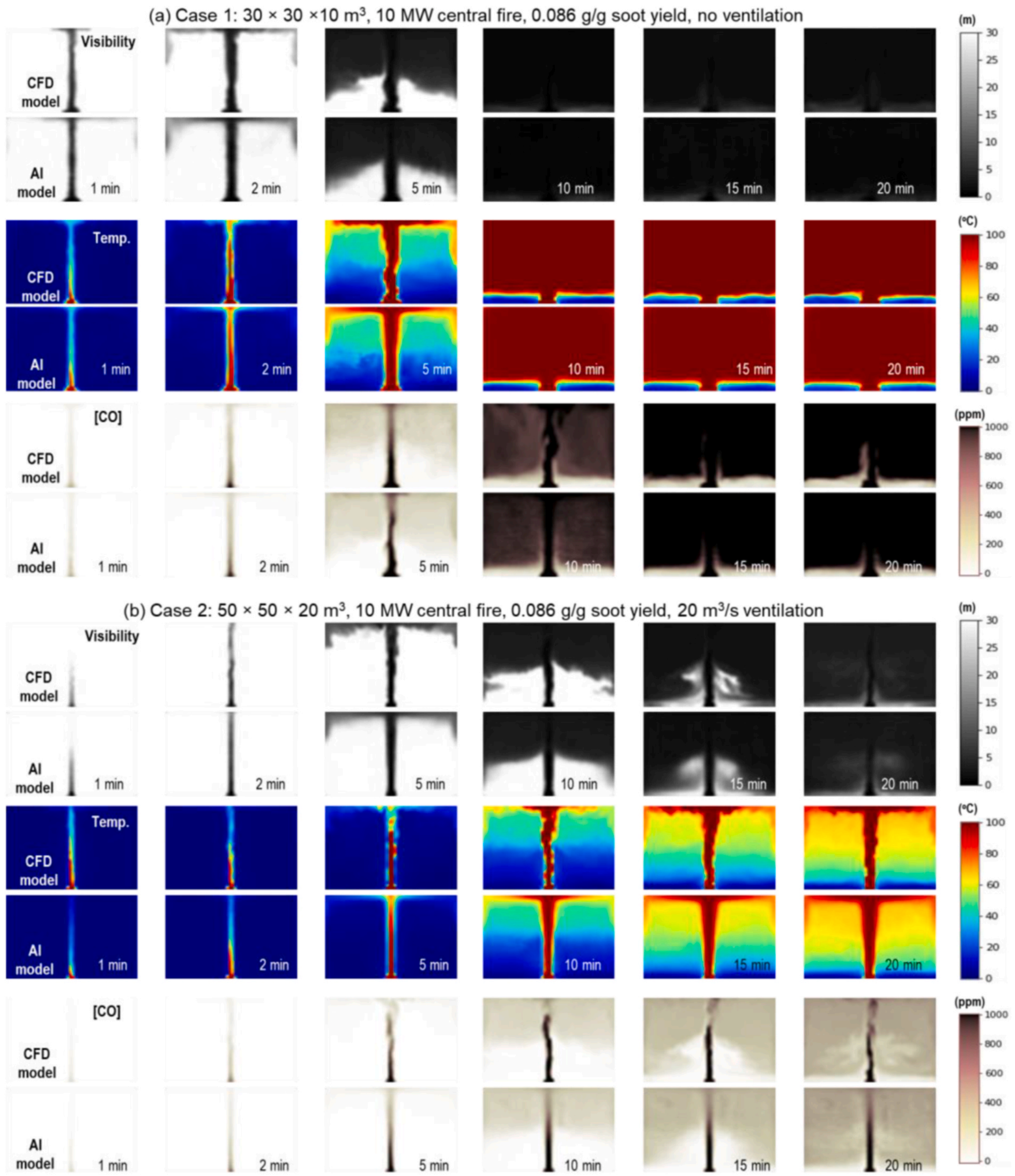

Fig. 6. Comparison of the actual (CFD simulation) and predicted (AI model) tenability profiles at different times after ignition under various fire scenarios: (a) 30 × 30 × 10 m^3 atrium with 10 MW HRR of central fire and 0.086 g/g soot yield and no smoke ventilation; (b) a larger atrium of 50 × 50 × 20 m^3 and ventilation increases to 20 m^3/s; (c) fire location moves to "Side" and soot yield further increases to 0.130 g/g (see Videos S1-S3).

average height of tenability limits at the region near the wall, instead of the whole atrium space, is often calculated to compare with the design requirement in practice, considering that the smoke descending from the ceiling is faster along the wall. The same strategy is also adopted in this paper.

Supplementary video related to this article can be found at https://doi.org/10.1016/j.csite.2022.102483

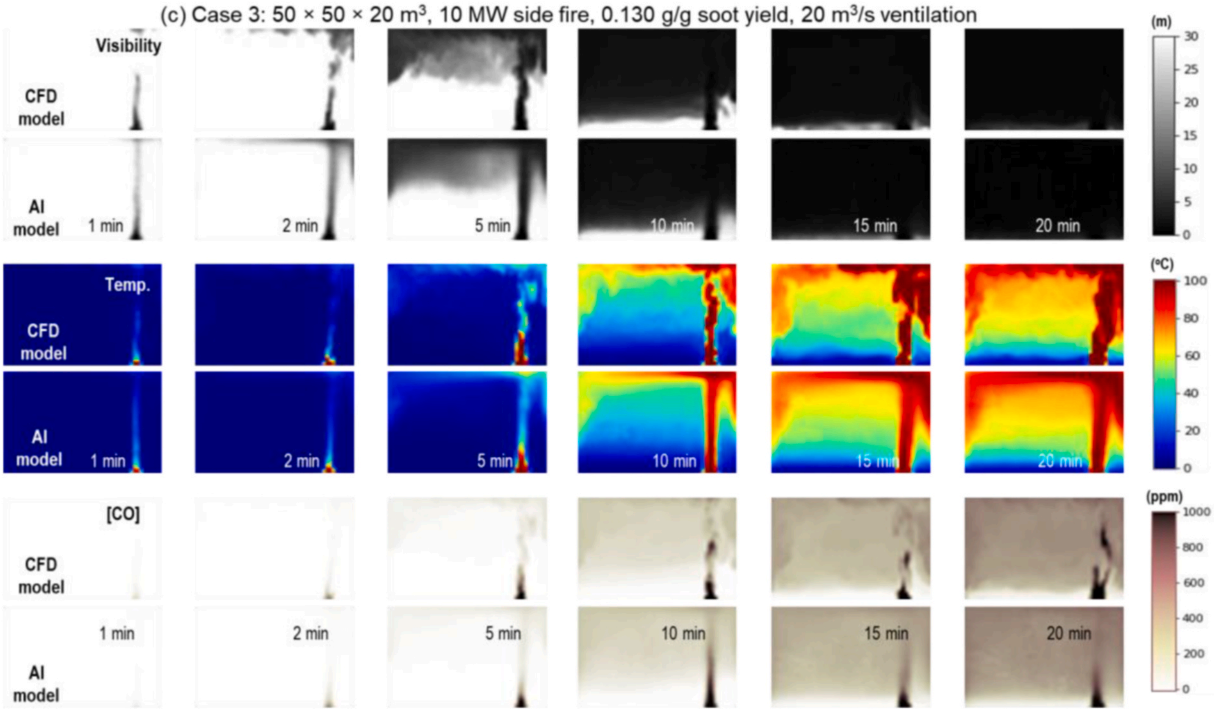

Fig. 6. (*continued*).

The evolvement of visibility, temperature and CO concentration limits can be calculated based on the tenability profile. Fig. 7a–c shows the performance of different criteria in each case. In each curve, the initial height before the fire is the atrium height. Overall, it is always visibility which firstly reaches the tenability limit at the clear height level, while the hazard of CO is less concerned. Although the CO keeps accumulating within the atrium, the overall concentration maintains below 600 ppm outside the plume area if ventilation is provided. It is excepted since CO normally presents potential hazards in a smaller or confined room instead of a large space of the

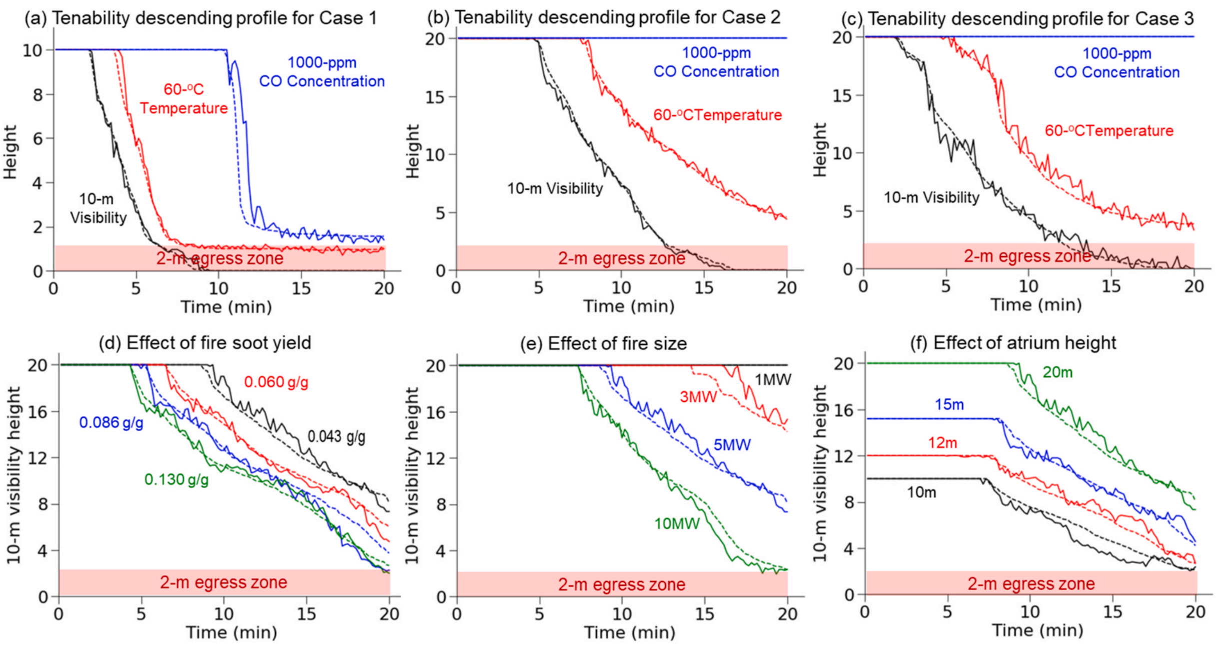

Fig. 7. Tenability descending profiles in (a) Case 1; (b) Case 2; and (c) Case 3; and the effects of (d) fire soot yield; (e) fire size; and (f) atrium height on the 10-m visibility result for a benchmark case with 70 m atrium length and 10 m^3/s ventilation, where the solid lines show the CFD fire simulations, and the dashed lines show the AI predictions.

atrium. On the other hand, when the geometry is relatively small without a ventilation system, the visibility and temperature have similar descending profiles, and both reached the tenability limit at the clear height (Fig. 7a). However, the temperature condition has a more significant improvement than the visibility condition after introducing some design optimization (Fig. 7b). With more design parameters changed, the difference between visibility and temperature profiles also changed, which indicates a different sensitivity of these criteria to the design parameters.

To further demonstrate the AI model performance under different design conditions, for a bench scenario with 70 × 70 × 20 m^3 atrium with 5 MW HRR of central fire and 0.043 g/g soot yield, and a 10 m^3/s smoke ventilation, Fig. 7d–e shows the evolvement of 10 m-visibility influenced by different soot yield, fire size, and atrium height. After 5–10 min, this visibility height drops rapidly since the smoke exhaust capacity has been reached, and the smoke began to fill the atrium space. As expected, the soot yield significantly influences the smoke visibility, and lower visibility is achieved with a higher soot yield at the same moment (Fig. 7d). For the prediction of fire scenarios not included in the database, e.g., the atrium with 0.060 g/g soot yield in Figs. 7d, and 12 m and 15 m height shown in Fig. 7f, the prediction performances are still promising. The overall coincidence of the predicted and simulated results once again proves the AI model's capacity to predict the fire-induced tenability evolvement inside an atrium.

4.2. Feasibility of predicting complex atriums

In practice, the atriums' appearance and layout could be much more complex than those simulated and trained cases. Although the database will be continuously updated with more complicated geometry, it is impractical to form a complete database having all the potential designs of the atrium. If the fire prediction for a simple atrium layout can provide a similar result to the one having more complex geometry, it could significantly broaden the application range of the tool and reduce the establishing time of the comprehensive database. In this section, new atriums with a roof shape (Fig. 2b) and slab extensions (Fig. 2c) are examined to check AI's feasibility in providing an estimation of smoke visibility descending profile for more complicated and unseen scenarios.

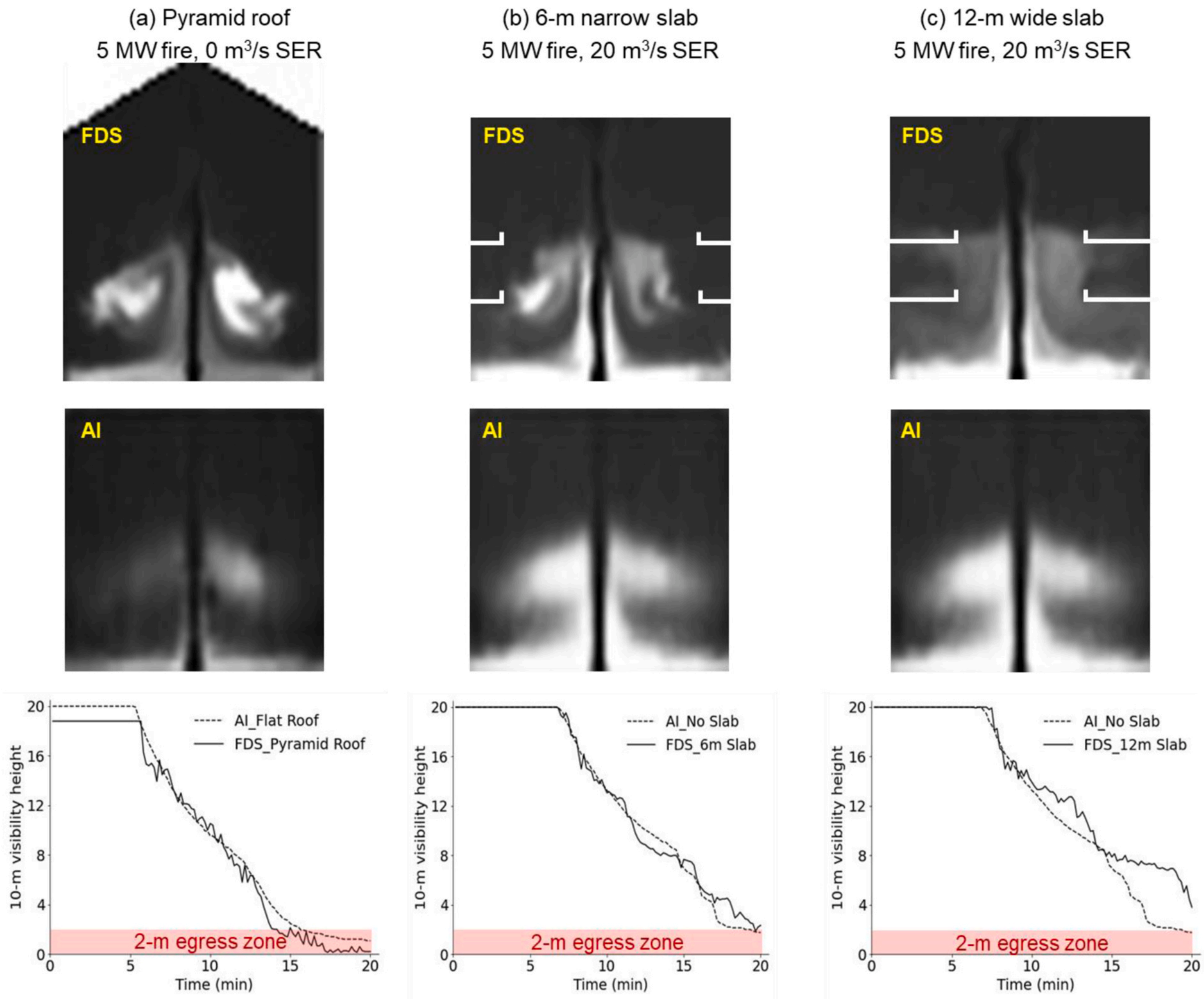

Fig. 8. Comparison of the simulated and AI predicted visibility for complex atriums: (a) with a pyramid roof, (b) with slab extension of 6 m, and (c) with slab extension of 12 m (see Video S4).

Atrium with a pyramid roof. Assume that an atrium is designed to have a square edge length of 50 m and a height of 18 m, and the atrium is designed to have a 6 m-height pyramid roof in addition (Fig. 2b). The total volume of the atrium equals that of a box-shaped atrium having the same floor area and a height of 20 m. Doors on the ground floor could be considered open to allow air exchange while no mechanical smoke exhausting system is provided. The combustible material is wooden cribs with a soot yield of 0.043 g/g, and the fire severity would not exceed 5.0 MW. The fire could be considered located at the center.

Fig. 8a compares the simulation result of the atrium with a pyramid roof and the predicted results of the AI model for the equivalent box-shaped atrium in terms of volume. The smoke visibility for the pyramid roof atrium initiates from the height of the lower box-shaped portion of 18 m. The complete comparison is given in the animation of Video S4. The comparison illustrates that the visibility descending trends are similar especially for the first 13 min when the smoke movement was not significantly disturbed by the air entrainment. This similarity would be mainly attributed to their same volume, and the influence of the roof can be implicitly considered by adopting an equivalent volume. It is also agreed with the experimental results which show the configuration of the roof has minor impacts on the smoke layer growth [60]. The growing discrepancy at the later stage of the simulation can be minimized by providing more training resources with different geometries to AI.

Atrium with slab extensions. Slab extensions are common for the atrium in large shopping malls. The feasibility of the fire safety design of such atriums using the proposed AI model is examined by adding slab extensions of 6 m or 12 m to original box-shaped atriums (Fig. 2c). A similar fire scenario, like that of the atrium with a pyramid roof, is considered. While a mechanical ventilation system having an SER of 20 m^3/s at the ceiling is provided here.

Fig. 8b compares the simulation result of the atrium with four 6-m slab extensions and the predicted results of the AI model for the same atrium without slab extensions (also see Video S4). Again, the good agreement of the visibility descending profile can be found in the first half of the simulation time, while the difference occurs at the later stage. When the depth of the slab increased by a factor of 2, Fig. 8c demonstrates a more considerable difference in the smoke descending trend between the simple and complex geometries.

Supplementary video related to this article can be found at https://doi.org/10.1016/j.csite.2022.102483

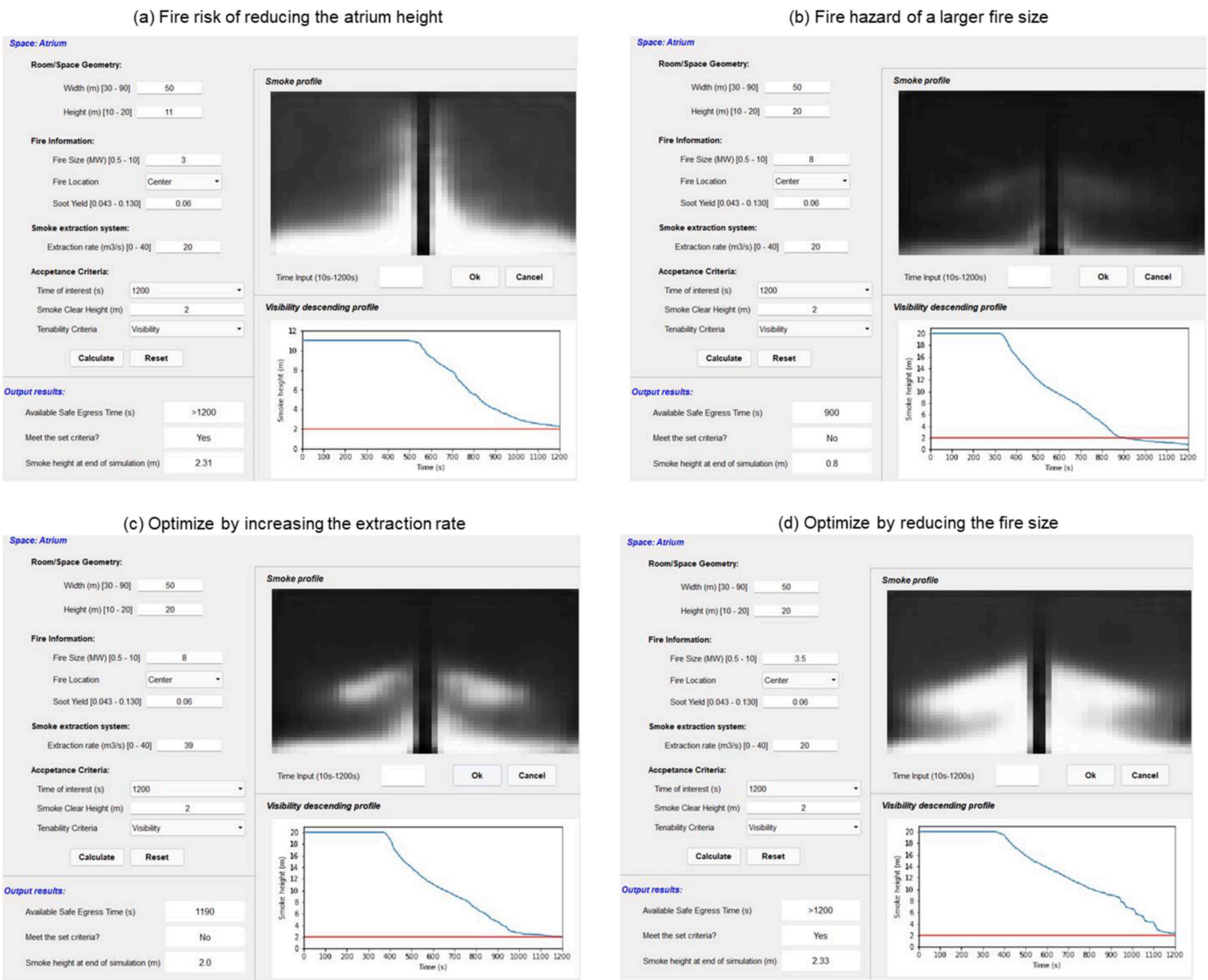

Fig. 9. The assessment of the atrium fire safety with IFETool, (a) lowering atrium height, (b) increasing the fire size, (c) optimizing the design by increasing the smoke extraction rate, and (d) reducing the fire size (open access at http://ifetool.firelabxy.com/).

As expected, the results show that the influence of slab extensions on visibility increases with the increase of extension length. The CFD simulations in both Fig. 8b and c have a stair-shaped visibility profile. On the one hand, the slab would prevent smoke to move down until it reaches the edge of the slab. On the other hand, the airflow movement is constrained by the slab extensions, leading to a higher upward air entrainment flow rate compared to the scenario without slabs, which slows down the smoke descending trend to some extent. This effect grows when the slab extension is longer.

The above demonstration presents the potentiality of the AI model in applying for some unseen scenarios than those having been trained. However, it also reveals a larger discrepancy in AI's prediction for more complicated geometries, especially when the smoke movement is significantly affected. Although the real slab design in atrium is more complex, the database can also include more cases with different configurations in future to improve the accuracy of AI predictions.

5. Building fire safety design practices with IFETool

In this section, the implementation of the developed IFETool for practical fire engineering PBD is demonstrated for typical consulting cases, such as determining the needed atrium height, the maximum fire size, and the limiting clear height. After inputting the required information, the pre-trained IFETool can immediately give the evolution of the tenability profile inside the atrium to help judge and optimize the performance of fire engineering design.

The most widely needed function of the PBD is to judge if the proposed atrium design can achieve an ASET of 1200 s or not (i.e., Pass or Not Pass). Herein, the visibility profile is presented to evaluate ASET under different design conditions, since it introduces the most server condition in most of the scenarios. The results of temperature and CO concentration can be checked by changing the tenability criteria in the user interface. As an example, a box-shaped atrium with a base length of 50 m and a height of 20 m is given. There is a reception designed at the center of the atrium, which is burning with an HRR of 3 MW, and the soot yield of the burning materials is 0.060 g/g. Is a mechanical smoke exhaust system with an extraction rate of 20 m^3/s sufficient to ensure an ASET of 1200 s? In Section 3.2, Fig. 4b shows the 10-m visibility profile at 1200 s and the evolution of the visibility profile of this base case. In the output sub-window, IFETool further quantifies that the 10-m visibility height at 1200 s is 3.6 m, which is higher than the required 2 m clearance. Thus, the proposed fire engineering design can pass the required performance.

5.1. Case 1: is it safe to reduce atrium height?

One of the common PBDs for the atrium is to improve the usage efficiency of the building by reducing the atrium height, so the top space of the original atrium can be released for additional utilization. For example, if the owner or stakeholder of the shopping mall would like to conduct renovation work to reduce the atrium height from 20 m (i.e., the base case in Fig. 4b) to 11 m and release the top space for a new 3-floor function room. As the geometry of the atrium has been changed, a review of the life safety level of the new design is required.

With the IFETool, the following steps can be made to assess the proposed renovation design promptly and provide remedial measurements.

- Input the updated geometry size (i.e., reducing the height to 11 m) and other design information.
- Click the "Calculate" button; the software will tell whether the current design is acceptable from the fire safety viewpoint (see Fig. 9a).

The AI engine shows that reducing the atrium high can still maintain the clearance height of 2.31 m at 1200 s, which is slightly larger than the required 2 m. Verification with a CFD simulation also gives the same result, but it takes many hours. However, compared to the base case in Fig. 4b, the safety margin is significantly reduced for the new design, and there is a range of uncertainty due to the modelling grid setup. Thus, to further improve fire safety after renovation, it is recommended to reduce flammable materials and fuel load on the atrium floor to reduce the fire size.

5.2. Case 2: how to handle the increase in building fuel load?

To celebrate the festival, the shopping mall plans to replace the center reception with a new exhibition with a 16 m^2 area. The typical fire intensity of solid fuel is about 500 kW/m^2 [61], so the fire HRR of the new exhibition area becomes 8 MW. Such an increase in the fuel load requires a review of the existing fire strategy. The IFETool will be used to assist the review and propose new fire protection measures. Fig. 9b shows that by increasing the fire HRR from 3 MW to 8 MW, the ASET value drops to 900 s, and at 1200 s, the 10-m visibility profile drops to 0.8 m. In other words, untenable conditions are reached, when the new exhibition area is proposed. With this IFETool, the AHJ can quickly identify the increased fire risk and ask for additional fire protection measures.

With the IFETool, fire engineers can also provide a quick calculation for possible design improvements to meet the design criteria, e.g., increasing the smoke extraction system or reducing the exhibition area. With a few trial calculations, the limiting design conditions can be obtained in a few minutes. Specifically, the minimum smoke extraction rate by the mechanical ventilation system is 39 m^3/s, as shown in Fig. 9c. The maximum fire HRR that the existing ventilation can handle is 3.5 MW, so the maximum area of the problem exhibition area is 7 m^2, as demonstrated in Fig. 9d. Comparatively, to find out these limiting conditions with CFD fire simulations, it could take a group of engineers and many days of repeated trial runs.

5.3. Case 3: a higher smoke clear height

To facilitate the visitors' experience, a 2 (wide) $\times$ 10 (length) m^2 area of the small platform (0.8% of floor area) will be added to the atrium as a rest area at the height of 5 m above the ground. Then, the minimum smoke clear height of the atrium would increase from 2 m to 7 m above the ground floor level to satisfy the ASET requirement. To assess the safety risk of adding the mezzanine, inputting the fire scenario information with the updated smoke clear height (i.e., 7 m). By clicking "Calculate", Fig. 10a shows that the ASET decreases to 1020 s (i.e., lower than the required 1200 s), and the 10-m visibility height at 1200 s drops to 3.6 m (<7 m). Thus, the proposed design cannot maintain a tenable condition when the required smoke clear height is increased.

The most common fire engineering design approach is to upgrade the mechanical ventilation system to increase the ASET. With the IFETool, try to input a higher extraction rate value until the design satisfies the criteria is met. As a result, a minimum smoke extraction rate of 30 m^3/s can be found for the renovation design, as shown in Fig. 10b. Further increasing the capacity of smoke extraction rate can increase the safety margin of ASET, which improves the chance of approval from the AHJ.

5.4. Perspectives of AI-driven design approaches

After introducing the capability of IFETool, there are key features for the different aspects of using the conventional CFD fire modelling approach and AI-driven approach in fire engineering PBD are summarized in Table 2. For example, conventional CFD modelling was adopted as a tool to verify if the equivalent performance of fire code can be attained. A limited number of fire scenarios were simulated for verification because it is costly and time-consuming to run these fire simulations with millions of cells, e.g., it takes about 48 h to finish a 70 m × 20 m (2.5 million-cell) atrium simulation with a 32-core server [3]. For the same reason, the design limits, such as the maximum fire size, the minimum smoke extraction rate, and the maximum soot yield, as well as the correlations between these design parameters, are not determined, which requires much more simulations. Without quantitative guidance, it is also challenging for the AHJ to evaluate a performance-based design since all the detailed design parameters such as design scenarios, design fires and acceptance criteria are suggested by engineers from case to case, which can lead to inconsistent safety levels for similar buildings [23].

On the other hand, the proposed deep-learning software, IFETool, can find if the proposed design is fire safe or not within a few seconds due to its super-fast calculation. Consequently, the design limits and the compensation of different design parameters can be obtained with a few trial calculations within a few minutes. For example, how much the smoke ventilation rate needs to increase to cope with the increase in HRR (see Section 5.3). Then, the design optimization can be achieved by quantifying the safety margins and reducing unnecessary systems.

Moreover, the AI-driven approach could provide overall strategies and limits for building fire safety in all design stages. During the concept design stage, the architect can be assisted by fire engineers to make key decisions via the tool, such as atrium size. During the approval process, the AHJ can use the AI tool to verify the proposed design of the smoke ventilation system and fire compartmentation. The critical issues could be identified by AI, and in turn, AI can also give certain information to resolve these fire safety issues.

As a start-up of the smart fire safety design, the scenario addressed by the current version of IFETool is relatively simple compared to the practical engineering cases. Still, the software can provide a quick reference for the early concept study while not all the design details are necessarily determined. It can monitor the overall safety level of the design schemes and minimize the design revisions caused by fire safety issues in the later design stage. In the future, the proposed IFETool will continuously be upgraded to include more modules for different building types, such as underground spaces and tunnels. Accordingly, the size of the CFD fire simulation database will also be increased to include more design parameters and features to meet the practical engineering demands, such as more building shapes, natural ventilation, air mark-up configuration and time-dependency HRRs. Another limitation of this start-up software is that only CFD simulation results are included in the database, and the database can also include experimental data from valuable large-scale fire tests for further training and validation. Moreover, the fire safety criteria can be adjusted to be adapted for fire safety design practices. The value of RSET can be modified to another time, e.g., 1800 s, according to the requirement from the local

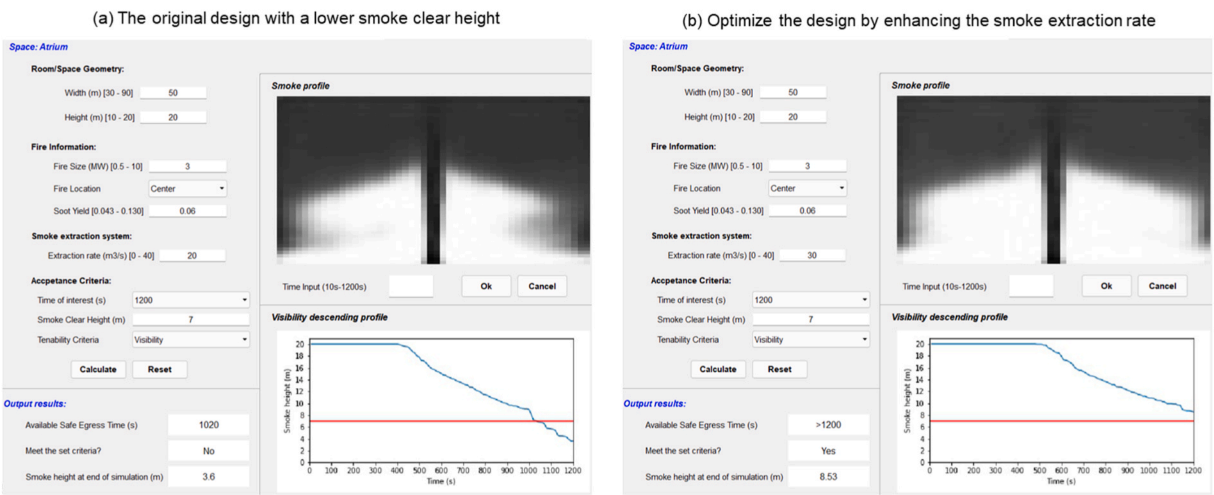

Fig. 10. The assessment of the fire engineering design with a higher smoke clear height: (a) the original design fails the new requirement; (b) optimized design by enhancing the smoke extraction rate.

Table 2
Comparison of design aspects between conventional modelling and AI-based model.

Aspects	Design by conventional CFD modelling	Design by AI prediction
Design approach	Provide several typical fire scenarios that can pass the regulation at the later stage, when the architectural designs are fixed.	Provide quick results for many cases that can quickly find design limits of fire protection systems and the architectural designs
Time spent	**Preparation:** Hours and days of model construction based on the complexity of the architectural design. **Running:** Hours to Days of CFD simulations **Redesign:** Repeat the above process.	**Preparation:** Months to form the CFD fire database, and years to continuously upgrade. **Running:** Seconds and minutes to get the design results and limits.
Accuracy and reliability	Results depend on the accuracy of CFD fire modelling and assumptions, as well as the engineers' experiences.	Results are comparable to the CFD fire simulations and limited by the accuracy of the original CFD fire database.
Consistency	Even in the same case, different engineers may provide different results (e.g., ASETs).	Results based on the same AI model are consistent for all users.
Design team viewpoints	Only a limited number of fire simulations can be conducted. Thus, it is often difficult to achieve required performances or find optimal design solutions, especially after architectural designs are fixed in the later stage.	The team can evaluate the acceptance level of the design with a similar case in the AI database at the very early stage (scheme design period), which provides great design feasibility.
AHJ viewpoints	Difficult to check and trust results, because cases that fail to pass the criteria are often not included in the report. Simulation parameters might be tuned (e.g., soot yield, radiation, etc.) by the designer to provide a better result.	Easy to reassess the result and parameters to find the worst scenario, but it takes time for AHJ to accept new AI methods.
Stakeholder viewpoints	Unable to evaluate whether the proposed design is cost-effective or not and discover the over-designs.	Easy to find design limits of building fire safety and optimize the design to be more cost-effective.
Overall cost	The simulation results and knowledge are not inherited. The entire design & review process is costly and largely repeated.	The knowledge can be inherited with a bigger building and fire database, and the trained AI will be more and more accurate and powerful.

AHJ. More criteria, such as the heat flux and air velocity, can be added to the options of the criteria. The exploration of alternative deep learning algorithms and functions might further improve the performance of the tool and address the limitation of the datasets. Considering the performance of the AI model depends on the database, our database is available on request and welcome more dataset from different parties to further increase its scope and accuracy.

6. Conclusions

This study develops an AI-driven software, named Intelligent Fire Engineering Tool (IFETool), to speed up the processes of building fire safety performance-based design (PBD) and assessment. As a demonstration, an extensive CFD modelling database is firstly established with a total of 1080 atrium fire scenarios by considering the critical building and fire information, including geometry length and height, fire location, severity and soot yield, ventilation, and post-ignition time.

The database is subsequently utilized for training a deep learning AI model which can achieve the prediction of tenability evolution with 97% accuracy. With the pre-trained AI model, the software is then able to assess fire safety designs proposed by the users in terms of smoke visibility, gas temperature, and CO concentration, within 1 s. Moreover, the proposed AI model can be applied to assess the spatial-temporal tenability profiles accurately for the atrium with different roof shapes and narrow slab extensions.

The implementation of IFETool is illustrated through three typical fire engineering practices. The software is proven to be capable of assessing the design safety, identifying the design limitation, and giving quick and reasonable suggestions to accelerate the reviewing of architectural designs. In the future, the IFETool will be further developed and upgraded to include other types of buildings and fire safety criteria to provide quick, accurate, and flexible building fire engineering solutions.

CRediT authorship contribution statement

Yanfu Zeng: Investigation, Writing - original draft, Formal analysis.
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Ling-chu Su: Investigation, Formal analysis, Resources.
Xiqiang Wu: Writing - original draft, Investigation, Methodology, Formal analysis.
Huang Xinyan: 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.

Data availability

Data will be made available on request.

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