World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

WJAETS
World Journal of Advanced Engineering Technology and Sciences

(Research Article)

Innovative AI-driven software for fire safety design: Implementation in vast open structure

Ruchit Parekh [1,*] and Charles Smith [2]

[1] *Department of Engineering Management, Hofstra University, New York, USA.*
[2] *Department of Computer Science, Hofstra University, New York, USA.*

World Journal of Advanced Engineering Technology and Sciences, 2024, 12(02), 741–750

Publication history: Received on 05 July 2024; revised on 11 August 2024; accepted on 14 August 2024

Article DOI: https://doi.org/10.30574/wjaets.2024.12.2.0345

Abstract

Fire modeling plays a crucial role in building fire safety assessments, yet it often incurs significant costs. This research introduces an AI-driven software, the Intelligent Fire Engineering Tool (IFETool), designed to accelerate fire safety evaluations and efficiently determine design constraints. Initially, a comprehensive numerical database focusing on atrium fires was established, accounting for key building and fire-related parameters. A deep learning model was then trained to forecast the progression of tenable smoke visibility, temperature, and CO levels with an impressive accuracy of 97%. The descending tenability profile was subsequently analyzed to estimate the available safe egress time (ASET) and to evaluate the fire safety of atriums with intricate roof designs and slab extensions. This AI tool enables swift assessments of proposed atrium fire engineering designs and offers valuable suggestions for potential improvements. Lastly, operational guidelines for IFETool are provided, catering to common atrium fire safety design tasks.

Keywords: Smart Building; Fire Engineering; AI Fire Design; Fire Safety; AI Software; Fire AI Design; Fire Design; AI Safety; Fire Engineering

1. Introduction

Historically, building fire safety has predominantly relied on prescriptive approaches, governed by established regulations and codes that set baseline safety requirements [12]. These regulations are designed to be flexible enough to meet the needs of various stakeholders, including architects, consultants, and clients [5]. However, while these codes are periodically reviewed and updated, significant changes are often only implemented following major fire incidents.

In the current era of rapid urbanization and the emergence of innovative architectural designs and materials, the demand for more sophisticated fire safety strategies has grown [4]. Traditional methods are increasingly inadequate to address the complex risks posed by modern buildings. As a result, performance-based design (PBD), which is grounded in engineering principles, has gained significant traction in recent years [6]. PBD allows for the incorporation of advanced scientific insights into fire and smoke dynamics, as well as human behavior during fires. Unlike the prescriptive approach, PBD can be tailored to meet specific design goals, such as sustainability, smart city integration [7], and the pursuit of cost-effective solutions as determined by stakeholders.

1.1. Challenges and Approaches in Performance-Based Design (PBD)

The rise of Performance-Based Design (PBD) in building fire engineering is rooted in the advancing scientific comprehension of fire behavior and the rapid evolution of computational tools. These tools, such as computer-aided design (CAD), zone models, computational fluid dynamics (CFD), and pedestrian modeling software, have become essential in predicting and analyzing fire and smoke dynamics. Examples include the Fire Protection Engineering Tool

* Corresponding author: Ruchit Parekh

(FPETool), Consolidated Model of Fire and Smoke Transport (CFAST), Fire Dynamics Simulator (FDS), FireFoam, AtriumCalc, and Pathfinder, many of which have been developed since the early 1990s [9]. These tools have undergone rigorous validation through extensive full-scale experiments, particularly in building and tunnel fire scenarios, where strong correlations between experimental and simulation data were observed, particularly in the far field of fire plumes.

Currently, these computational tools are widely accepted as industry benchmarks during the design phase of buildings [10]. Fire engineers utilize them to assess smoke control systems, evaluate fire protection responses, determine evacuation paths, and gauge overall fire safety levels [11]. Despite their widespread use, several challenges persist in applying these tools to PBD:

- **Complexity of Fire Phenomena:** Simulating a fire event is inherently complex, requiring numerous inputs and sub-models within fire modeling software. Inappropriate model setups are common and demand extensive peer reviews from both internal and external sources to ensure accuracy.
- **High Costs and Expertise Requirements:** Implementing PBD, particularly with CFD fire modeling, is resource-intensive and costly. It demands significant computational power and extensive training, which poses challenges for junior designers who may find it difficult to master.
- **Limited Exploration of Design Limits:** Due to the high computational costs, only a limited number of fire scenarios are typically simulated, restricting the ability to fully explore design limits. Much of the computational work is repetitive and tedious.
- **Skepticism of Model Validity:** Authorities Having Jurisdictions (AHJ) often question the validity and reliability of fire models and simulation results. Identifying specific design issues remains time-consuming and challenging, even when the source code is provided.

As design regulations and paradigms evolve, particularly for specific infrastructures like airports and underground facilities, the application of fire engineering PBD has become an expensive and often prescriptive approach. These challenges undermine the potential benefits and credibility of PBD in practical fire safety design.

1.2. Leveraging AI in Fire Safety Design

Recent advancements in Artificial Intelligence (AI), particularly in deep learning algorithms, have demonstrated significant potential to transform building fire safety design, structural fire resistance [18], and fire detection and response systems. Machine learning techniques have been employed to model fire processes, delivering results that are comparable to those obtained from Computational Fluid Dynamics (CFD) simulations during both steady and dynamic stages. Moreover, when integrated with the Internet of Things (IoT), AI models can not only pinpoint the location and severity of a fire but also predict its development, support evacuation planning, and assess structural resilience to fire, providing real-time alerts that are unattainable with traditional CFD simulations [1].

Recently, AI-powered design and auditing tools have been developed to assist in verifying compliance with architectural CAD drawings and prescriptive fire safety regulations [8]. Despite these advancements, uncovering the intricate relationships between building and fire design parameters and their impact on fire evolution and safety remains challenging without expensive numerical simulations [2]. Our recent research has shown the feasibility of using deep learning algorithms alongside a pre-established CFD fire database to accurately predict smoke behavior within simple atrium structures and estimate the Available Safe Egress Time (ASET) within seconds [3]. These neural network-based models can provide preliminary assessments, reducing the number of fire simulations needed to evaluate fire safety performance, validate simulation results, and enhance efficiency. Additionally [19], AI tools can help authorities swiftly assess the reliability of PBD, review CFD fire simulations, and identify potential issues. Ultimately, AI has the potential to update current fire safety codes, making building fire safety more cost-effective.

This paper builds on our previous work by incorporating an enhanced AI model into the Intelligent Fire Engineering Tool (IFETool) software, designed to streamline fire engineering PBD. The IFETool integrates a pre-trained deep learning AI engine [20], developed from an extensive CFD fire simulation database covering a wide range of fire scenarios [21]. The tool’s accuracy and efficiency are demonstrated through the fire safety PBD of various atrium designs, with practical methods and procedures for using the software illustrated through typical consulting practice scenarios [22].

2. Development of the AI Model

2.1. CFD Simulation

The construction of the AI model begins with the use of Computational Fluid Dynamics (CFD) simulations, which are a widely utilized method for analyzing fire growth and smoke movement within the framework of Performance-Based Design (PBD) for building fire safety [13]. These simulations typically employ the Fire Dynamics Simulator (FDS) developed by NIST. For this study, large, simplified atrium structures were selected for demonstration purposes, with several critical atrium fire safety parameters being varied throughout the process.

- **Fire Size:** The fire's size, or heat release rate (HRR), is a critical factor affecting total smoke production. This study considered seven different peak HRR values (0.5, 1, 2, 3, 5, 8, and 10 MW) while maintaining a consistent HRR per unit area of 0.5 MW/m^2. A fast-growing t2 fire model with a growth rate of 0.0469 kW/s^2 was used in each scenario until the peak HRR was reached.
- **Fire Location:** The location of the fire source plays a significant role in the behavior of the fire plume and the movement of smoke. Two fire source locations were simulated: one at the center of the atrium and the other near the sidewall.
- **Soot Yield:** The amount of soot produced by a fire varies depending on the type of combustible material involved. To cover different scenarios, three soot yield values were selected: 0.043, 0.086, and 0.130 g/g.
- **Building Geometry:** Given that real-world building geometries can be complex, a simplified box-shaped geometry was assumed for the atriums in the training database. The atrium floor was modeled as a square with edge lengths ranging from 30 m to 90 m, encompassing atrium volumes from 9,000 m^3 to 162,000 m^3. Two atrium heights (10 m and 20 m) were also considered.
- **Smoke Extraction Rate (SER):** The SER impacts visibility and tenable conditions within the atrium. Depending on the atrium's volume, smoke control systems may not be necessary to maintain tenable conditions, but authorities may still perceive high fire risks. Five smoke extraction rates (0, 10, 20, 30, and 40 m^3/s) were evaluated to address different design needs.

In total, 1,080 fire scenarios were simulated to generate a comprehensive training database. The simulations assumed an ambient temperature of 25 °C and used a fuel mixture of natural materials and plastic compounds. Vents were defined to represent mechanical smoke extraction systems, and natural air make-up was provided through four entrances at the atrium's bottom level, following common engineering practices [16]. Each fire simulation lasted for 1,200 seconds, allowing for adequate consideration of practical egress times. Vertical profiles were established to track the evolution of visibility, temperature, and CO concentration within the atrium. The grid resolution, a crucial setting in FDS, was determined based on the non-dimensional parameter ($D^*/\delta x$) to ensure accuracy. A grid size of 0.4 m was applied to all simulations, balancing speed and precision. The total number of cells ranged from 140,625 to 2,531,250, depending on the atrium's volume, and the simulations were executed on a 32-core server, with each scenario taking between 12 and 24 hours to complete.

2.2. Database Creation and AI Model Training

Following the completion of the simulations, the results and associated fire scenario parameters were compiled into a comprehensive database, which served as the foundation for training the AI model. Key building and fire design parameters—such as atrium length and height, fire location, fire size, soot yield, smoke extraction rate, and post-ignition time (or burn duration)—were systematically used as inputs for the model [15]. The database includes a total of 1,080 scenarios. Post-ignition times were recorded at 10-second intervals to account for variations in the tenability profile throughout the 1,200-second simulation period. This resulted in 129,600 data samples per criterion, derived from multiplying the number of scenarios by the number of post-ignition intervals.

Tenability profile records, which include visibility, temperature, and CO concentration at specific vertical slices (y-plane), were extracted using an in-house middleware called "fds2ascii." These records were then converted into a uniform format for subsequent training and display, with tenability images scaled down to 50 × 50 pixels. The data were randomly divided into three subsets: a training dataset (60%), a validation dataset (20%), and a testing dataset (20%). The training dataset was used to identify and learn the hidden correlations between design parameters and tenability outcomes, while the validation dataset provided feedback for fine-tuning the model's hyperparameters during the training process. The testing dataset was employed to evaluate the model's prediction accuracy once the training was complete.

For visibility, the output range was set between 0 m and 30 m, while temperature and CO concentration outputs ranged from 25 °C to 1,040 °C and 0 ppm to 5,646 ppm, respectively. Due to the significant differences in these ranges, each criterion was trained separately using its own 129,600 data samples to prevent interference during training. Despite normalization, the AI model's predictions for temperature and CO concentration initially showed less accuracy. This was likely because the upper limits for these criteria were set too high, particularly near the flame, making it difficult for the model to accurately recognize lower values outside the fire plume. To address this, temperature records were reprocessed with a threshold of 100 °C to better identify the 60 °C tenability limit, and a threshold of 1,000 ppm was set for CO concentration. These adjustments improved the AI model's ability to distinguish relevant distributions.

The AI model was built using a Convolutional Neural Network (CNN) architecture, enhanced with Transposed Convolutional Neural Network (TCNN) layers, which are known for converting lower-dimensional input data into higher-dimensional spaces [16]. Previous research has demonstrated the effectiveness of TCNN in predicting fire-induced temperature fields and smoke movement. The detailed architecture of the AI model was refined based on earlier work. The model's performance was measured using mean squared error (MSE) as the loss function, which quantifies the difference between CFD simulations and AI predictions, and the coefficient of determination (R^2) to assess prediction accuracy. The model was trained over multiple iterations [17], with training samples processed in small batches to optimize efficiency and stability given the server's memory constraints. Once fully trained, the model's network structure and layer weights were ready for practical deployment.

3. IFETool Software

3.1. Conceptual Design

The Intelligent Fire Engineering Tool (IFETool) is a software application that integrates the deep-learning AI engine proposed in this study to assist in building fire engineering design. The conceptual framework of this intelligent tool. The primary objective of IFETool is to leverage AI to predict the tenability profile over time and evaluate whether the proposed fire engineering PBD meets the necessary tenability criteria. The foundation of this tool is the creation of a comprehensive database encompassing a wide range of fire scenarios. Conducting extensive CFD fire simulations across different building types, design features, and fire protection systems is a crucial first step [17].

In its initial version, IFETool 1.0 focuses exclusively on atrium fires, for which a large atrium fire database was established, as described in Section 2.2. This database was used to train the AI model. The accuracy and performance of IFETool are heavily dependent on the quality of this database and the training of the deep learning model [14]. Future versions of IFETool will expand the database to include more fire scenarios and a variety of building types. The user interface of IFETool was designed to be user-friendly, facilitating easy input and visualization of output results. Users are required to input essential parameters related to fire safety design, including building details, fire scenarios, and safety criteria. The model then generates predictive results and displays them on the user interface.

3.2. User Interface and Operation

The current version, IFETool 1.0, is accessible online (http://ifetool.firelabxy.com/). The operation panel of the IFETool, which comprises four main sections: input fields, output results, tenability profile visualization, and smoke height curve display. After manually entering the required parameters, this AI software visualizes the distribution of selected criteria at a specific moment, shows the progression of tenability over time, and determines whether the current fire design satisfies the PBD criteria, such as whether the Available Safe Egress Time (ASET) exceeds the Required Safe Egress Time (RSET). The input parameters include design details for both fire and building,

Once all inputs are entered and the "Calculate" button is clicked, IFETool calls upon the pre-trained AI model to predict the tenability profiles. The descending smoke height is also calculated and displayed within one second. Users should be aware that, due to the application of a 0.4 m grid size in the numerical training database, the predicted results come with an uncertainty range of 0.4 m, as the values within a grid are uniform [18]. This uncertainty arises from the accuracy limitations of the CFD simulations, which can be mitigated by applying a safety margin. To start a new case, users can simply click the "Reset" button to clear all inputs and outputs [19].

It is recommended that the input parameters for each scenario be set within the ranges. Specifically, the fire source can be placed either at the "Center" or "Side" of the atrium. The values for atrium length, height, SER, fire size, soot yield, and post-ignition time should also fall within their corresponding ranges: [30, 90] m for length, [10, 20] m for height, [0 m^3/s, 40 m^3/s] for SER, [0.5, 10 MW] for fire size, [0.043, 0.130 g/g] for soot yield, and [0, 1,200 s] for post-ignition time. However, the AI tool's pattern recognition capabilities are robust enough to provide rough estimates for atriums with more complex roof structures and slab extensions, even if they are not included in the training database (as discussed in Section 4.2). Additional input parameters will be incorporated as the fire database expands.

Currently, IFETool 1.0 evaluates criteria such as smoke visibility, gas temperature, and CO concentration, which are commonly used in practical projects. Future upgrades of the software will include additional criteria, such as heat flux and air velocity, to accommodate various design safety objectives. Additional features, such as exporting input information and predicted results to a CSV file and a user guide under the "Help" button, will be added to enhance functionality. The IFETool software has been filed for a patent and will be continuously maintained and updated. It aims to deliver quick and accurate results for professional fire engineers, similar to traditional tools like FPETool and AtriumCalc, which analyze smoke control systems in atriums and provide initial values for CFD fire modeling. However, users should recognize that the accuracy of IFETool is limited by the underlying CFD simulation database, and interpret the results accordingly.

4. Validation and Performance

4.1. Evaluation of the AI Model's Performance

This section evaluates the AI model's performance using the training database. The progression of the Mean Squared Error (MSE) loss and the coefficient of determination (R^2) throughout the training process. The results indicate that the MSE stabilizes at a near-constant value of 0.0053 after 380 training epochs, with the corresponding R^2 converging to 97%. Although the training accuracy becomes quite high around 50 epochs, the model was fully trained over 500 epochs to achieve optimal performance, ensuring that the loss continued to decrease and the accuracy continued to improve. The high accuracy, nearing 100%, demonstrates that the AI model is highly effective in resolving the spatial variations in smoke visibility.

A comparison between the simulated and predicted tenability profiles (derived from the 20% test set), showcasing the AI model's capability in predicting spatially resolved critical values. The comparison is shown at various time intervals following ignition for a fire scenario involving a 30 × 30 × 10 m^3 atrium with a 10 MW HRR central fire, a soot yield of 0.086 g/g, and no smoke ventilation (Case 1). Darker pixels indicate poorer tenability at specific locations. The AI model effectively recognizes the cylindrical fire plume above the fire source, where safety levels are compromised, and accurately reproduces the descending smoke layer from the ceiling to the designed smoke clear height. As expected, the AI model overlooks fluctuating and turbulent smoke eddies, which have no significant impact on assessing tenable conditions (see detailed comparison in Video S1).

A scenario where smoke ventilation is increased to 20 m^3/s in a larger atrium measuring 50 × 50 × 20 m^3 (Case 2, Video S2). The improved tenability conditions (i.e., safer regions) benefit from the expanded smoke reservoir and increased smoke extraction, with CO concentration being the most significantly affected. The introduction of the ventilation system complicates the air movement within the space, leading to strong air entrainment and turbulent vortex structures, especially in the later stages of the simulation when the smoke layer approaches the air inlets. The AI model simplifies these turbulent boundaries, as they showed negligible relevance to the final design criteria during training. Given that the primary goal of the tool is not to analyze the underlying mechanisms of fire dynamics, this simplification allows for quicker result predictions. A scenario where the fire location is moved to the side, and the soot yield is increased to 0.130 g/g (Case 3, Video S3). Although the result is more complex than a symmetrical profile, the AI model accurately predicts its evolution and boundaries.

According to common practice acceptance criteria, visibility of at least 10 meters, a temperature below 60 °C, and CO concentration under 1,000 ppm should be maintained at 2 meters above the floor level within 20 minutes to ensure safe egress . In practice, the design team may define the smoke clear height at a higher position to minimize smoke damage during a fire. Conservatively, the average height of tenability limits near the walls, rather than the entire atrium, is often calculated to compare with design requirements, considering that smoke descends more rapidly along the walls. The same approach is adopted in this paper.

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

The comparison of actual (CFD simulation) and predicted (AI model) tenability profiles under various fire scenarios, and The performance of different criteria in each case. Each curve begins with the initial atrium height before the fire. Overall, visibility is typically the first criterion to reach the tenability limit at the clear height level, while the hazard posed by CO is less concerning. Although CO continues to accumulate within the atrium, the overall concentration remains below 600 ppm outside the plume area if ventilation is provided. This is expected, as CO generally poses greater risks in smaller or confined spaces rather than in large atriums. On the other hand, in scenarios where the atrium is relatively small and lacks a ventilation system, both visibility and temperature have similar descending profiles, reaching tenability limits at the clear height. However, the temperature condition shows more significant improvement than visibility after introducing some design optimizations. As more design parameters are adjusted, the difference between visibility and temperature profiles also changes, indicating varying sensitivities of these criteria to the design parameters.

To further demonstrate the AI model's performance under different design conditions, The benchmark scenario with a 70 × 70 × 20 m^3 atrium, a 5 MW HRR central fire, a soot yield of 0.043 g/g, and a 10 m^3/s smoke ventilation rate. The 10-meter visibility height drops rapidly after 5–10 minutes, as the smoke exhaust capacity is reached, and smoke begins to fill the atrium. As expected, soot yield significantly affects smoke visibility, with higher soot yields resulting in lower visibility at the same time interval. For fire scenarios not included in the database, such as atriums with a 0.060 g/g soot yield and atriums with 12-meter and 15-meter heights, the AI model's predictions remain promising. The overall agreement between predicted and simulated results further confirms the AI model's ability to accurately predict the evolution of fire-induced tenability within an atrium

4.2. Feasibility of Predicting Complex Atrium Designs

In practice, atriums can have much more complex shapes and layouts than the scenarios used in training and simulation. While the database will continue to be expanded to include more intricate geometries, it is unrealistic to create a database that encompasses all possible atrium designs. If fire predictions for simple atrium layouts can yield results comparable to those for more complex geometries, this would significantly expand the tool's applicability and reduce the time needed to develop a comprehensive database. In this section, we examine new atrium designs with pyramid-shaped roofs and slab extensions to assess the AI model's ability to estimate smoke visibility profiles in more complex and previously unseen scenarios.

Atrium with a Pyramid Roof: Consider an atrium with a square floor plan measuring 50 meters on each side, a height of 18 meters, and an additional 6-meter-tall pyramid-shaped roof. The total volume of this atrium is equivalent to that of a box-shaped atrium with the same floor area and a height of 20 meters. Doors on the ground floor are assumed to be open, allowing for air exchange, but no mechanical smoke exhaust system is provided. The combustible material is wooden cribs with a soot yield of 0.043 g/g, and the fire severity does not exceed 5.0 MW, with the fire located at the center of the atrium.

The simulation results of the atrium with the pyramid roof to the AI model's predictions for an equivalent box-shaped atrium in terms of volume. The smoke visibility in the pyramid roof atrium starts descending from the lower portion of the box-shaped atrium at 18 meters. A complete comparison is available in the animation in Video S4. The comparison shows that the visibility descending trends are quite similar, especially during the first 13 minutes when smoke movement is not significantly disturbed by air entrainment. This similarity can be attributed mainly to the equivalent volume, and the influence of the roof can be implicitly accounted for by adopting an equivalent volume. This finding aligns with experimental results, which indicate that roof configuration has minimal impact on smoke layer growth. The growing discrepancy observed later in the simulation could be minimized by training the AI model with more varied geometries.

Atrium with Slab Extensions: Slab extensions are common features in atriums within large shopping malls. To evaluate the feasibility of using the AI model for fire safety design in such atriums, slab extensions of 6 meters and 12 meters were added to the original box-shaped atrium. A similar fire scenario was used as in the pyramid roof case, but with a mechanical ventilation system providing a smoke extraction rate of 20 m^3/s at the ceiling.

The simulation results of the atrium with 6-meter slab extensions to the AI model's predictions for the same atrium without slab extensions (also available in Video S4). Once again, there is a strong agreement in the visibility descending profiles during the first half of the simulation, with differences becoming apparent in the later stages. When the slab extension length is doubled to 12 meters, A more noticeable divergence in the smoke descending trends between the simple and complex geometries.

As expected, the results indicate that the impact of slab extensions on visibility increases with the length of the extensions. The CFD simulations in a stair-stepped visibility profile. On one hand, the slabs delay the downward movement of smoke until it reaches the edge of the slab. On the other hand, the slab extensions restrict airflow, resulting in a higher rate of upward air entrainment, which slows the smoke descending trend to some extent. This effect becomes more pronounced as the slab extension length increases.

The above demonstration highlights the potential of the AI model to be applied to previously unseen scenarios beyond those included in the training dataset. However, it also reveals a larger discrepancy in the AI's predictions for more complex geometries, particularly when smoke movement is significantly affected. Although real-world slab designs in atriums are more intricate, the database can be expanded to include more cases with varied configurations in the future, improving the accuracy of AI predictions.

5. Implementing IFETool in Building Fire Safety Design Practices

This section demonstrates how the developed IFETool can be used in practical fire engineering Performance-Based Design (PBD) for typical consulting scenarios, such as determining the appropriate atrium height, the maximum fire size, and the limiting clear height. By inputting the required information, the pre-trained IFETool can instantly provide the evolution of the tenability profile within the atrium, helping assess and optimize the performance of the fire engineering design.

One of the most common PBD tasks is determining whether the proposed atrium design can achieve an Available Safe Egress Time (ASET) of 1,200 seconds (i.e., Pass or Not Pass). In this context, the visibility profile is used to evaluate ASET under different design conditions, as it often represents the most severe condition in various scenarios. Temperature and CO concentration results can also be evaluated by adjusting the tenability criteria in the user interface. For example, consider a box-shaped atrium with a base length of 50 meters and a height of 20 meters. A reception area is located at the center, burning with a Heat Release Rate (HRR) of 3 MW, and the burning materials have a soot yield of 0.060 g/g. Is a mechanical smoke exhaust system with a 20 m^3/s extraction rate sufficient to ensure an ASET of 1,200 seconds?

In Section 3.2, shows the 10-meter visibility profile at 1,200 seconds and the evolution of the visibility profile for this base case. In the output sub-window, IFETool further quantifies that the 10-meter visibility height at 1,200 seconds is 3.6 meters, which exceeds the required 2-meter clearance. Therefore, the proposed fire engineering design passes the required performance criteria.

5.1. Case 1: Is It Safe to Reduce Atrium Height?

A common PBD scenario involves improving building usage efficiency by reducing the atrium height, thereby freeing up the top space for additional use. For example, if the owner or stakeholders of a shopping mall want to reduce the atrium height from 20 meters to 11 meters to create a new three-floor function room, a review of the life safety level of the new design is required.

Using IFETool, the following steps can be taken to quickly assess the proposed renovation design and suggest remedial measures:

- Input the updated geometry (i.e., reducing the height to 11 meters) and other design information.
- Click the “Calculate” button; the software will indicate whether the current design is acceptable from a fire safety perspective.

The AI engine shows that reducing the atrium height can still maintain a clearance height of 2.31 meters at 1,200 seconds, slightly above the required 2 meters. Verification with a CFD simulation also produces the same result, though it takes several hours. However, compared to the base case, the safety margin is significantly reduced in the new design, and there is a range of uncertainty due to the modeling grid setup. Therefore, to further enhance fire safety after renovation, it is recommended to reduce flammable materials and the fuel load on the atrium floor to decrease the fire size.

5.2. Case 2: How to Manage Increased Building Fuel Load?

In preparation for a festival, the shopping mall plans to replace the center reception with a new exhibition area measuring 16 m^2. With a typical fire intensity of solid fuel around 500 kW/m^2, the fire HRR for the new exhibition area becomes 8 MW. This increase in fuel load necessitates a review of the existing fire strategy. The IFETool can assist in this review and suggest new fire protection measures. That by increasing the fire HRR from 3 MW to 8 MW, the ASET value drops to 900 seconds, and at 1,200 seconds, the 10-meter visibility profile falls to 0.8 meters. In other words, untenable conditions are reached when the new exhibition area is proposed.

With IFETool, the Authorities Having Jurisdictions (AHJ) can quickly identify the increased fire risk and request additional fire protection measures. Fire engineers can also use IFETool to quickly calculate possible design improvements to meet the criteria, such as increasing the smoke extraction system's capacity or reducing the exhibition area. After a few trial calculations, the limiting design conditions can be determined within minutes. Specifically, the minimum smoke extraction rate required by the mechanical ventilation system is 39 m^3/s . The maximum fire HRR that the existing ventilation can handle is 3.5 MW, so the maximum area for the exhibition should be 7 m^2. In contrast, determining these limiting conditions through CFD fire simulations would require a team of engineers and several days of repeated trial runs.

5.3. Case 3: A Higher Smoke Clear Height

To enhance visitors' experience, a small platform measuring 2 meters wide by 10 meters long (0.8% of the floor area) will be added to the atrium as a rest area at a height of 5 meters above the ground. Consequently, the minimum smoke clear height of the atrium would need to increase from 2 meters to 7 meters above the ground floor level to satisfy the ASET requirement. To assess the safety risk of adding the mezzanine, input the fire scenario information with the updated smoke clear height (i.e., 7 meters). By clicking "Calculate," The ASET decreases to 1,020 seconds (i.e., lower than the required 1,200 seconds), and the 10-meter visibility height at 1,200 seconds drops to 3.6 meters, which is less than the required 7 meters. Therefore, 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. Using IFETool, you can input a higher extraction rate value until the design meets the criteria. As a result, a minimum smoke extraction rate of 30 m^3/s can be identified for the renovation design. Further increasing the smoke extraction capacity can enhance the safety margin for ASET, improving the likelihood of approval from the AHJ.

5.4. Prospects of AI-Driven Design Approaches

After detailing the capabilities of IFETool, it's useful to compare the key features of conventional CFD fire modeling with AI-driven approaches in fire engineering PBD. Traditionally, CFD modeling has been used as a verification tool to ensure compliance with fire codes. However, only a limited number of fire scenarios are typically simulated due to the high cost and time-consuming nature of these simulations, which can involve millions of cells. For instance, simulating a 70 m × 20 m atrium with 2.5 million cells on a 32-core server might take about 48 hours to complete. Because of these constraints, it is often challenging to determine design limits such as the maximum fire size, minimum smoke extraction rate, and maximum soot yield, as well as the correlations between these parameters. Additionally, without quantitative guidance, it can be difficult for the AHJ to evaluate PBDs effectively, as design scenarios, design fires, and acceptance criteria are often suggested by engineers on a case-by-case basis, leading to inconsistent safety levels across similar buildings.

Conversely, the proposed deep-learning-based IFETool can determine whether a proposed design is fire-safe within seconds, thanks to its rapid calculation capabilities. Consequently, design limits and the interplay between various design parameters can be established through a few trial calculations in just minutes. For instance, the tool can quickly determine how much the smoke ventilation rate needs to be increased to accommodate a rise in HRR, as discussed in Section 5.3. This allows for design optimization by quantifying safety margins and eliminating unnecessary systems.

Moreover, the AI-driven approach offers comprehensive strategies and limits for building fire safety across all design stages. During the concept design stage, fire engineers can use the tool to assist architects in making key decisions, such as determining atrium size. During the approval process, the AHJ can use the AI tool to verify the proposed smoke ventilation system and fire compartmentation designs. AI can help identify critical issues and suggest solutions to address fire safety concerns.

Although the current version of IFETool addresses relatively simple scenarios compared to practical engineering cases, it can still provide a quick reference for early concept studies where not all design details have been finalized. The tool can monitor the overall safety level of design schemes and minimize the need for design revisions due to fire safety issues in later stages. In the future, IFETool will be continuously upgraded to include more modules for different building types, such as underground spaces and tunnels. The size of the CFD fire simulation database will also be expanded to include more design parameters and features, catering to practical engineering needs, such as diverse building shapes, natural ventilation, air make-up configurations, and time-dependent HRRs.

A limitation of this initial software version is that its database consists solely of CFD simulation results. In the future, the database could also incorporate experimental data from large-scale fire tests for further training and validation. Additionally, fire safety criteria can be adjusted to meet specific design practices. For example, the RSET value could be modified to 1,800 seconds or another time frame, depending on local AHJ requirements. More criteria, such as heat flux and air velocity, could also be added as options. Exploring alternative deep learning algorithms and functions might further enhance the tool's performance and address dataset limitations.

Since the performance of the AI model is closely tied to the database, our database is available upon request, and we welcome contributions from different parties to further expand its scope and accuracy.

6. Conclusion

This study introduces the Intelligent Fire Engineering Tool (IFETool), an AI-driven software designed to accelerate the processes of performance-based design (PBD) and assessment in building fire safety. As part of this development, a comprehensive CFD modeling database was created, comprising 1,080 atrium fire scenarios. This database incorporates key building and fire parameters, such as geometry dimensions, fire location, severity, soot yield, ventilation, and post-ignition time.

The database was then used to train a deep learning AI model capable of predicting tenability evolution with 97% accuracy. Leveraging this pre-trained AI model, IFETool can evaluate fire safety designs proposed by users in terms of smoke visibility, gas temperature, and CO concentration, delivering results within one second. Additionally, the AI model can accurately assess spatial and temporal tenability profiles for atriums with various roof shapes and slab extensions.

The application of IFETool is demonstrated through three typical fire engineering scenarios. The software has proven effective in evaluating design safety, identifying limitations, and providing rapid, insightful recommendations to streamline the review of architectural designs. Looking ahead, IFETool will continue to evolve, incorporating additional building types and fire safety criteria to offer fast, accurate, and adaptable fire engineering solutions.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] P. Stollard, Fire from First Principles (4th ed.), Routledge Taylor & Francis Group, London and New York, 2014. Available at: https://doi.org/10.4324/9781315852553.

[2] D.V. Chadderton, Building Services Engineering, Routledge, London, 2013. Available at: https://doi.org/10.4324/9780203121320.

[3] L.C. Su, X. Wu, X. Zhang, X. Huang, "Smart performance-based design for building fire safety: Prediction of smoke motion via AI," Journal of Building Engineering, vol. 43, 2021, p. 102529. Available at: https://doi.org/10.1016/j.jobe.2021.102529.

[4] M.J. Hurley, E.R. Rosenbaum, Performance-based Fire Safety Design, CRC Press, Boca Raton, 2015. Available at: https://doi.org/10.1201/b18375.

[5] J. Gales, B. Chorlton, C. Jeanneret, "The historical narrative of the standard temperature-time heating curve for structures," Fire Technology, 2020. Available at: https://doi.org/10.1007/s10694-020-01040-7.

[6] J.W. Park, O.K. Lim, W.J. You, "Effect of ignition heat source on design fire curve of polyethylene foam in a compartment fire," Case Studies in Thermal Engineering, vol. 22, 2020, p. 100790. Available at: https://doi.org/10.1016/j.csite.2020.100790.

[7] S. Deal, Technical Reference Guide for FPEtool Version 3.2, National Institute of Standards and Technology, 1995. NISTIR 5486-1.

[8] R.D. Peacock, W.W. Jones, P.A. Reneke, G.P. Forney, CFAST – Consolidated Model of Fire Growth and Smoke Transport (Version 6) User's Guide, 2005. Available at: https://doi.org/10.6028/nist.sp.1041.

[9] K. McGrattan, S. Hostikka, J. Floyd, R. McDermott, M. Vanella, Fire Dynamics Simulator Validation Guide (vol. 3), NIST Special Publication, 2006, p. 1018.

[10] Y. Wang, P. Chatterjee, J.L. De Ris, "Large eddy simulation of fire plumes," Proceedings of the Combustion Institute, vol. 33, 2011, pp. 2473-2480. Available at: https://doi.org/10.1016/j.proci.2010.07.031.

[11] J.H. Klote, AtriumCalc Atrium Smoke Control Calculator Technical Information and User Guide, 2014.

[12] H. Wang, Q. Chen, J. Yan, Z. Yuan, D. Liang, "Emergency guidance evacuation in fire scenes based on pathfinder," in Proceedings of the 7th International Conference on Intelligent Computation Technology and Automation, 2014, pp. 226–230. Available at: https://doi.org/10.1109/ICICTA.2014.62.

[13] J. Zhao, Z. Xu, H. Ying, X. Guan, K. Chu, S.M. Sakepa Tagne, et al., "Study on smoke spread characteristic in urban interval tunnel fire," Case Studies in Thermal Engineering, vol. 30, 2022, p. 101755. Available at: https://doi.org/10.1016/j.csite.2022.101755.

[14] C. Gutiérrez-Montes, E. Sanmiguel-Rojas, A. Viedma, G. Rein, "Experimental data and numerical modeling of 1.3 and 2.3 MW fires in a 20 m cubic atrium," Building and Environment, vol. 44, 2009, pp. 1827-1839. Available at: https://doi.org/10.1016/j.buildenv.2008.12.010.

[15] P. Ayala, A. Cantizano, E.F. Sánchez-Úbeda, C. Gutiérrez-Montes, "The use of fractional factorial design for atrium fires prediction," Fire Technology, vol. 53, 2017, pp. 893-916. Available at: https://doi.org/10.1007/s10694-016-0609-z.

[16] S. Hostikka, M. Kokkala, J. Vaari, Experimental Study of Localized Room Fires, 2001.

[17] C. Gutiérrez-Montes, E. Sanmiguel-Rojas, M.A. Burgos, A. Viedma, "On the fluid dynamics of the make-up inlet air and the prediction of anomalous fire dynamics in a large-scale facility," Fire Safety Journal, vol. 51, 2012, pp. 27-41. Available at: https://doi.org/10.1016/j.firesaf.2012.02.007.

[18] W.K. Chow, S.S. Li, Y. Gao, C.L. Chow, "Numerical studies on atrium smoke movement and control with validation by field tests," Building and Environment, vol. 44, 2009, pp. 1150-1155. Available at: https://doi.org/10.1016/j.buildenv.2008.08.008.

[19] P. Ayala, A. Cantizano, G. Rein, G. Vigne, C. Gutiérrez-Montes, "Fire experiments and simulations in a full-scale atrium under transient and asymmetric venting conditions," Fire Technology, vol. 52, 2016, pp. 51-78. Available at: https://doi.org/10.1007/s10694-015-0487-9.

[20] P. Ayala, A. Cantizano, G. Rein, C. Gutiérrez-Montes, "Factors affecting the make-up air and their influence on the dynamics of atrium fires," Fire Technology, vol. 54, 2018, pp. 1067-1091. Available at: https://doi.org/10.1007/s10694-018-0725-z.

[21] J. He, X. Huang, X. Ning, T. Zhou, J. Wang, R.K. Kit Yuen, "Modeling fire smoke dynamics in a stairwell of high-rise building: Effect of ambient pressure," Case Studies in Thermal Engineering, vol. 32, 2022, p. 101907. Available at: https://doi.org/10.1016/j.csite.2022.101907.

[22] Code for Fire Protection Design of Civil Airport Terminal, 2018.