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Applications of artificial intelligence in enhancing building fire safety

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Abstract

In the last ten years, the integration of big data and artificial intelligence (AI) has introduced innovative smart technologies within the building and construction sectors. AI is increasingly being applied to fire detection, risk evaluation, and fire prediction. This chapter outlines a roadmap for incorporating AI into building fire safety engineering, drawing comparisons to the evolution of Computational Fluid Dynamics (CFD) fire modeling. It offers guidelines for developing a comprehensive fire database, using both experimental and simulated data. The chapter also explores AI algorithms with significant potential for detecting and forecasting fire scenarios, and reviews recent advancements in intelligent firefighting systems. Lastly, three new concepts for utilizing AI in building fire safety are proposed:

- AI-driven fire engineering design for enhancing structural fire safety,
- the implementation of a building-fire Digital Twin for real-time fire risk and development monitoring, and
- the Super Real-time Forecast (SuRF) for predicting fire progression.

Keywords: Artificial intelligence; Building fire safety; Fire detection; Risk assessment; Fire forecasting; Computational Fluid Dynamics (CFD); Fire engineering design; Digital Twin; Intelligent firefighting; Super Real-time Forecast (SuRF)

1. Introduction

Urban infrastructure plays a crucial role in defining contemporary human societies. The density, scale, condition, and intricacy of this infrastructure are strong indicators of socio-economic progress at both national and global levels. Globalization, rapid urbanization—particularly in developing nations—and the expansion of the wildland-urban interface (WUI) have contributed to an increased risk of devastating fires in densely populated urban areas. These fires pose significant challenges to fire safety design, firefighting, emergency response, and recovery. For instance, the 2017 Grenfell Tower fire in London claimed over 70 lives, and the 2018 California Camp Fire resulted in at least 85 fatalities while destroying over 18,000 structures. Today, the societal cost of fire is estimated to be 1-2% of the global annual GDP, a figure closely linked to both GDP per capita and the Human Development Index. As a result, more industrialized countries and regions likely face higher costs associated with fire damage.

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Figure 1 Fire Pattern

High-density urban areas depend on intricate, interconnected infrastructures—such as high-rise buildings, tunnels, and underground spaces—where densely populated areas push the limits of infrastructure resilience during urban disasters. These infrastructures are especially vulnerable to major fire-related disruptions, such as facade fires and the growing incidence of global WUI fires, along with secondary hazards like large-scale urban fires triggered by earthquakes. Innovative approaches are therefore essential to build resilience against such events.

In the last decade, advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), cloud and edge computing, and sensor and communication networks have steadily been integrated into the building and construction industry. While most AI applications in fire engineering have centered on fire detection, fire risk evaluation, and structural analysis, only a handful of studies have used AI to predict fire behavior within compartments and tunnels. For example, Hodges et al. utilized a transpose convolutional neural network (TCNN) in combination with Fire Dynamics Simulator (FDS) data to estimate temperature distribution in compartment rooms. Arjan and colleagues employed logistic regression to predict flashover occurrences in compartments, using factors such as fuel thickness, burning intensity, and duration. Similarly, Wang et al. used machine learning techniques to forecast flashover in compartment fires, drawing from a simulation database. Lee et al. compared several models and demonstrated the effectiveness of faster regional CNNs in fire detection, significantly reducing false alarms. More recently, Wu and collaborators have explored deep learning AI methodologies for detecting and forecasting critical fire events in tunnels.

Currently, the majority of a city's fire safety budget is allocated to firefighting efforts (i.e., response) and post-fire investigations and reconstruction (i.e., recovery), particularly in wildland-urban interface (WUI) areas. In contrast, pre-fire preparation receives much less attention, a challenge that exists globally. As shown in Fig. 2, incorporating AI technology could reduce fire safety expenditures and make spending more efficient. AI could enable smarter infrastructure design, thereby lowering fire risks. Additionally, AI can assist in monitoring fire progression and guiding evacuations, allowing firefighters to be better equipped to handle rapidly evolving fire situations, extinguish fires more quickly, rescue more individuals, and minimize casualties. Ultimately, this would reduce both the loss of life and property damage, minimizing reconstruction costs. In line with Murphy's Law—"whatever might happen, will happen"—the best course of action is to enhance preparedness, and AI offers a more intelligent way to do so.

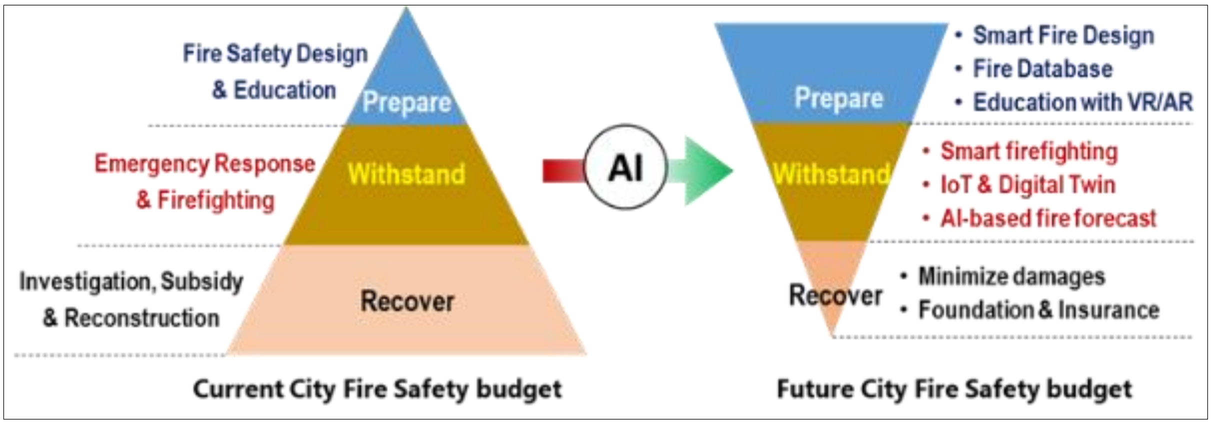

Figure 2 The vision of the AI's role in shaping the fire safety of the future city

This chapter explores the latest advancements in AI applications for fire safety engineering, drawing comparisons with Computational Fluid Dynamics (CFD) applications. It also reviews recent developments in fire databases and AI algorithms for reconstructing fire scenarios. Furthermore, three novel concepts for applying AI in building fire safety are proposed: (1) AI-driven fire engineering design to enhance structural fire safety, (2) the building-fire Digital Twin for real-time fire risk monitoring and development tracking, and (3) Super Real-time Forecast (SuRF) for predicting fire progression.

2. Foundations of AI-based Fire Engineering

2.1. AI vs. CFD in Fire Engineering

The concept of artificial intelligence (AI) was first introduced in 1956, aiming to use computer algorithms to perform specific tasks like language processing, data storage, and pattern recognition. However, progress in AI's development and its applications has not always been consistent, unlike traditional research fields such as Computational Fluid Dynamics (CFD). The gap between the high expectations for AI and the limited computational resources led to two "AI winters"—one in the 1970s and another in the late 1980s—when research funding for AI was significantly reduced.

The third wave of AI research began in the early 2000s, spurred by advancements in powerful computer hardware and new algorithms. Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which mimic the human brain, became prevalent in academia and industry. Unlike traditional machine learning models, deep learning's greatest strength lies in its ability to automatically extract features, though it requires large and diverse datasets for training. Despite AI's widespread use in scientific and engineering research, there remains the question of whether another "AI winter" is on the horizon. Currently, AI's role in fire safety is still nascent, requiring more interdisciplinary research. However, AI has the potential to revolutionize traditional fire safety research, firefighting strategies, and promote the vision of resilient cities and smarter emergency response systems.

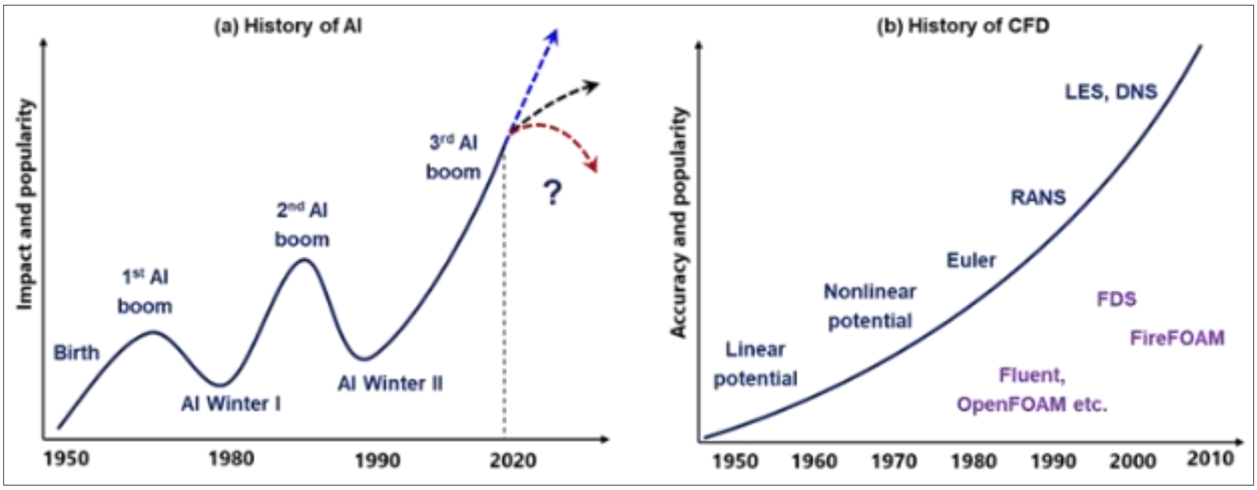

Figure 3 The history of (a) AI research, and (b) CFD and application in fire engineering

To comprehend AI's role in building fire safety, we can compare it to the adoption of CFD by the fire community over the past few decades (see Table 1). Historically, fire engineering relied on empirical formulas and correlations derived from experimental data. These empirical laws, supported by analytical and scale modeling, guided fire research and education. Since the late 1990s, CFD tools like the Fire Dynamics Simulator (FDS) by NIST and FireFOAM by FM Global have transformed fire engineering. Today, CFD tools are routinely used in fire engineering analysis (FEA) and performance-based design (PBD), particularly in innovative architectural projects such as skyscrapers, large atriums, and long tunnels. CFD fire modeling is now an integral part of fire engineering education, fire investigations, and research.

It's important to note that the primary users of CFD fire engineering tools are fire safety engineers and scientists, not the mathematicians or computer scientists who develop the underlying equations or software. Although there are challenges with accuracy and reliability, users with a strong understanding of fire dynamics and fire engineering principles can effectively utilize CFD fire models to analyze fire behavior and support fire safety design. Similarly, AI is expected to become a valuable tool in future fire engineering applications, research, and even firefighting, with fire engineers and researchers being the primary users rather than AI or computer scientists. Developing AI tools for the fire safety community will require collaboration between computing and IT professionals, firefighters, regulators, and policymakers. Fire engineers are also encouraged to understand AI algorithms to better assess the reliability and limitations of AI outputs, rather than viewing AI as a "black box."

Furthermore, AI's future applications in fire safety are expected to extend beyond those of conventional CFD tools. One significant limitation of CFD fire modeling is the lengthy and expensive computational process, especially for large or complex buildings. Consequently, CFD modeling is mostly used for PBD, fire investigations, and research where time is less of a critical factor. Even in these areas, only a limited number of CFD simulations are performed due to constraints on computational power and cost. Moreover, CFD simulations are typically conducted on a case-by-case basis without building a shared database, which limits the knowledge exchange among the fire research community. CFD also has little to no role in firefighting and emergency response, as it cannot generate real-time information, even with advanced computing resources.

In contrast, data-driven AI technologies, supported by big data, IoT, drones, and advanced communication systems, can overcome these challenges. AI can address these issues by (1) creating large experimental and numerical databases to train powerful AI systems and (2) utilizing AI models, informed by real-time data from IoT systems connected to fire scenes, to provide rapid fire forecasts. This capability can significantly aid firefighting operations and emergency decision-making by delivering real-time insights.

Table 1 Facts and Predictions

	Facts of CFD applications in fire	**Predictions of AI applications in fire**
Principle	Solving partial differential equations	Pattern matching with the database
Process Process time	Geometry Boundary & Initial Conditions → CFD → Temporal & spatial of flow, smoke, temperature Hours - Days	Building & Fire → AI + Database → Temporal & spatial of flow, smoke, temperature Seconds - Minutes
Development	Mature & commercialized	Early stage
Users	Led by fire experts (not by CFD experts)	Led by fire experts (not by AI experts)
Fire Safety design	Widely used in the building fire safety performance-based design (PBD)	Smart AI-based building fire safety design will be the future trend
Fire forecast	Rarely used to predict real fire events (costly and questionable)	Enable Fire prediction and forecast based on big fire database and digital twin
Firefighting	Difficult to support the firefighting (slow computation and not real-time)	Play a key role in the smart firefighting (data-driven and real-time forecast)

2.2. Establishing a Fire Scenario Database

A comprehensive and reliable training database is essential for developing effective AI models in fire safety. To enable AI systems to detect hidden features of fire behavior, the database needs to be both large and diverse, representing various fire parameters and scenarios. This can be achieved by considering the influence of different factors during fire tests and simulations. Typically, constructing such a database involves several steps: (1) gathering data by reviewing available literature and extracting useful information, (2) pre-processing the data through quality checks, removal of outliers and noise, and filtering, and (3) applying data mining techniques to extract valuable insights.

Due to the complex nature of fire data, properly storing, managing, and analyzing such large datasets remains challenging. Much of the fire test data, particularly for commercial products, is not publicly available. Moreover, the fire research community has traditionally been reluctant to share data, making it difficult to build a comprehensive fire database. To address this, it is crucial to develop global standards and guidelines for organizing, presenting, and sharing fire research data, promoting a collective effort across the community. Some initiatives, such as the IAFSS working group on Measurement and Computation of Fire Phenomena (MaCFP), have made strides in collecting experimental and numerical data for fire modeling validation and verification. However, new efforts to establish databases specifically for AI applications in fire safety are necessary moving forward.

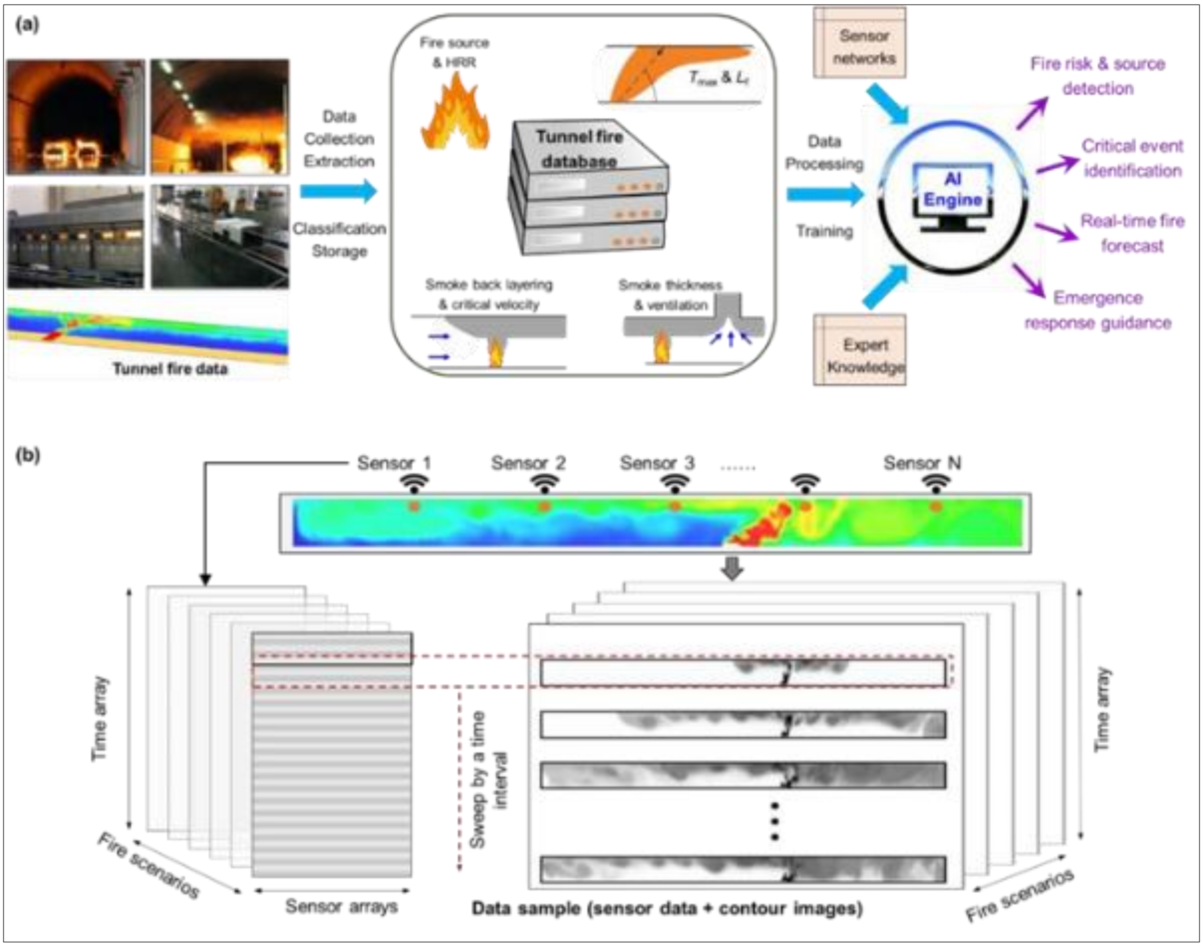

Figure 4 Fire Scenario Database

2.3. Experimental Fire Database

In a typical fire test, multiple parameters are measured, and the data is categorized into two main types. The first category is sensor data, which includes measurements like temperature from thermocouples or heat detectors, smoke detection, CO and CO2 levels from gas detectors, and heat flux from radiometers or plate thermometers. Sensors are often placed in various locations to capture long-term data, resulting in time-series data with both spatial and temporal dimensions. The second category is visual data, which includes video footage from closed-circuit television (CCTV) or infrared cameras inside the building. This visual data also extends to footage from airborne cameras carried by drones or airplanes, as well as processed satellite images, particularly useful for monitoring large-scale fires in urban areas, wildland-urban interfaces (WUI), and informal settlements.

At present, databases are constructed using sensor data that is publicly accessible, such as those found in journal publications and technical reports. However, since much of the fire test data was not originally intended to be shared, extracting all the necessary information and comparing data across different sources can be extremely difficult. Figure 4 illustrates how a tunnel fire database can be constructed from published articles and reports. Through a detailed literature review, the data can be categorized based on key parameters for tunnel fires, such as fire size, smoke layer thickness, critical velocity, back-layer length, and plug-holing. After this categorization, all relevant experimental data are extracted. To facilitate easy searching within the database, all raw data and images should be systematically named, organized, and indexed, along with detailed descriptions. Given the complex and multi-factorial nature of fire behavior, providing sufficient context about the tests before processing the data is critical for effective database construction.

2.4. Numerical Fire Database

While obtaining comprehensive sensor data from full-scale fire experiments or real incidents is ideal, the current available tunnel fire data from literature are insufficient in size and organization to support deep learning applications. As an alternative, a database generated through extensive CFD-based numerical simulations can facilitate AI-driven fire forecasting. One widely used tool for such simulations is the open-source program Fire Dynamics Simulator (FDS) . Extensively validated and verified, FDS is a standard tool for performance-based fire safety design and research. The detailed temperature data produced by CFD models are especially useful for validating AI methods designed to predict fire behavior.

In numerical simulations, visual data includes contours and videos generated from the computational results. These time-sequenced data (e.g., images and videos) can offer a comprehensive view of the fire scenario, including the fire's real-time progression, evacuation processes, smoke and temperature distributions, and firefighting activities. Compared to the sensor data gathered from fire tests, the 2D and 3D numerical data are significantly larger in scale, offering far more intricate details about fire dynamics. In contrast, video data from fire tests are rare, often unshared, and typically lack consistency due to varying camera angles. Furthermore, the large size and complexity of test videos make them difficult to process and analyze scientifically.

Figure 4(b) outlines the process of constructing a numerical database for tunnel fires , where point sensor data matrices are coupled with 2D temperature contour data. This coupling is valuable because in practical fire tests and real-life applications, point temperature data from thermocouples are most commonly used. By combining limited experimental data with abundant, detailed numerical simulations, this approach enables the creation of a comprehensive database that integrates both types of information.

2.5. AI Methods for Detecting and Forecasting Fire

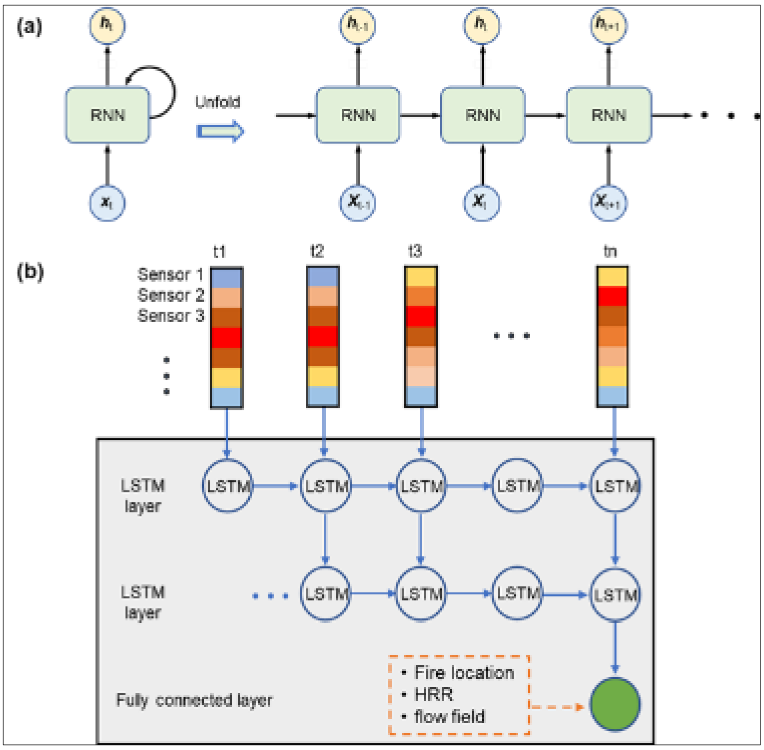

Figure 5 Fire Forecasting Database

In real building fire situations, hot, toxic, and fast-spreading smoke poses a greater danger than flames. The rapid spread of heat and smoke within confined spaces not only endangers lives but also complicates evacuation and firefighting strategies. Accurately and quickly identifying the fire's location and size is of great scientific and practical significance for guiding suppression and rescue efforts. However, during actual firefighting operations, determining the size and location of fire sources inside smoke-filled spaces is a significant challenge.

Recently, data-driven AI methods, especially artificial neural networks (ANNs), have been increasingly used in fire detection. For instance, Choi and Choi [6] developed a system that incorporates a flame detector with a visual light camera. Fire detection was treated as a nonlinear classification problem, which was addressed using a support vector machine (SVM) classifier. However, this method exhibited a high rate of false alarms. To address this, deep convolutional neural networks (CNNs) were introduced [32,33]. CNNs, without needing detailed feature extraction, were shown to automatically improve fire detection accuracy through deep learning. These deep CNNs have been effective in detecting fires in buildings using sensor data [34–37] and in identifying large-scale wildfires using geoinformatics data [38].

Recurrent neural networks (RNNs), specifically designed for predicting or classifying temporal data, are also used in fire detection. As shown in Fig. 5(a), RNNs are structured with a loop that unfolds into a sequence of interconnected cells. Importantly, these RNN cells represent the same cell in different states, rather than distinct cells. The time-sequential data is processed through this loop, preserving order-dependent information, which can then be interpreted to produce predictions. Although RNNs have been widely applied in fields like speech recognition [39], their primary limitation lies in their difficulty handling long sequences of data [40].

Long Short-Term Memory (LSTM) networks introduce a specialized internal structure that effectively handles sequential data through three key components: the forget gate, input gate, and output gate. These gates work together to decide how to process incoming information, selectively retaining or discarding data and determining how to output results. As data is sequentially imported, the LSTM retains useful information, updating it through the input and forget gates, and translates it into a structured output. LSTM networks are highly effective at solving complex prediction problems [42].

For instance, Wu et al. [18] developed a regression-based 2-layer LSTM network model to identify fire scenarios in tunnels (Fig. 5b). Using a numerical database as illustrated in Fig. 4(b), the LSTM unit in the input layer processes temperature vectors measured by sensors. The LSTM sequentially handles the incoming data and predicts a three-element vector representing the fire location, heat release rate (HRR), and ventilation speed, with an accuracy of 90%. To ensure the precision of AI-based fire detection, sensitivity analysis should be conducted to optimize the spatial-temporal configuration of sensors and database setup.

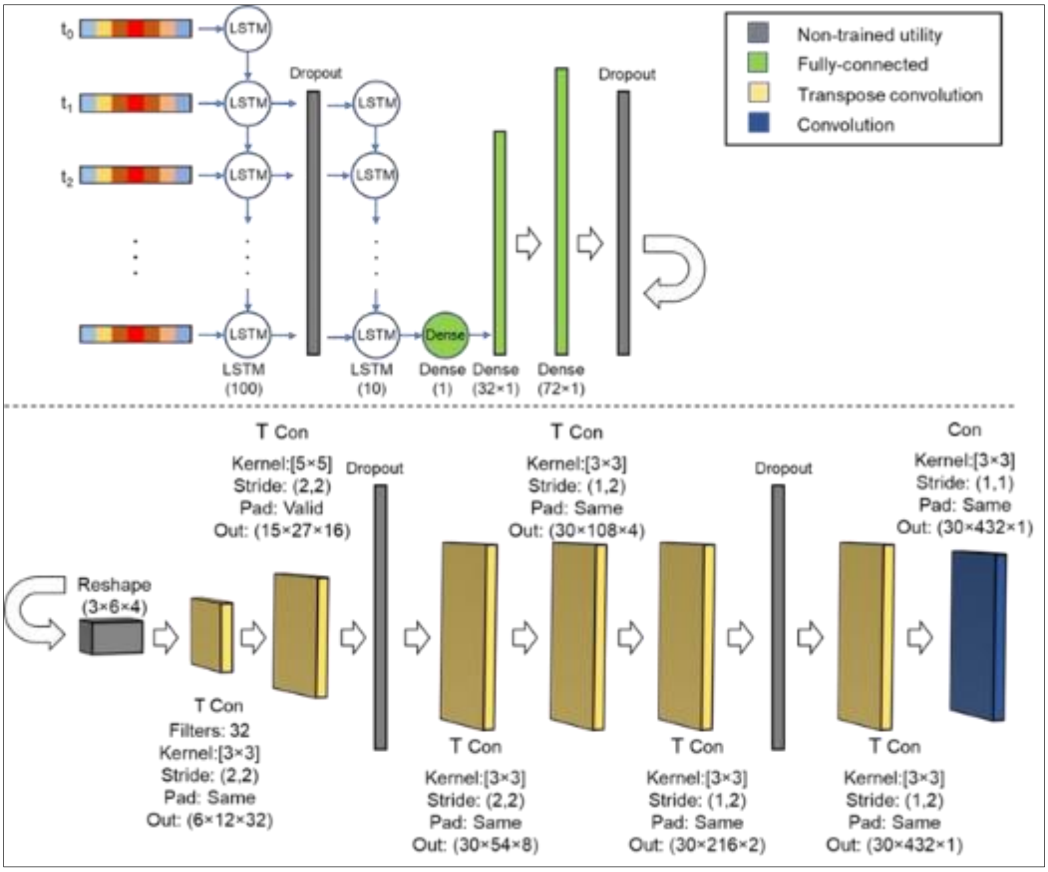

Figure 6 Fire Forecasting Database (A)

In addition to monitoring current fire scenarios, forecasting the future development of fires is crucial, especially in extreme temperature conditions that can rapidly evolve. To address this, a deep learning model combining an LSTM network with a transpose convolutional neural network (TCNN) was proposed. This model integrates LSTM, dense, and TCNN layers (Fig. 6) [20]. The input layer processes data structured as 32 (sensor count) × 30 seconds (data sample length). Two fully connected dense layers follow, enriched with additional neurons to extract further information from the LSTM layers. This setup enhances the model’s ability to forecast fire progression, potentially mitigating casualties and improving response strategies.

3. Applications of AI in Building Fire Safety

AI and big data hold significant potential for enhancing building fire safety, spanning the fire engineering design stage, daily fire-safety management, and smart firefighting during actual fire events. This section explores how these technologies can revolutionize each phase.

3.1. AI-Based Fire Engineering Design

Performance-Based Design (PBD) is an objective-oriented approach that moves beyond prescriptive fire safety codes. First emerging between the 1970s and 1990s, PBD allowed for more flexible architectural designs and the use of new construction materials, incentivizing fire research and tools such as CFD (Computational Fluid Dynamics) and evacuation models (Fig. 7a). Today, PBD is widely used by fire engineering consultancies worldwide and accepted by regulatory authorities (AHJ).

However, despite the flexibility PBD offers, it often ends up reducing construction costs instead of genuinely improving fire safety. Several issues with PBD practices are:

- **Low Design Fire Values**: Often, fires are modeled with low heat release rates (HRR) that may not represent real fire scenarios (typically less than 5 MW).
- **Unverified Smoke Management Systems**: Many smoke control systems have not been experimentally verified.
- **Overuse of Concepts**: The concepts of Available Safe Egress Time (ASET) and Required Safe Egress Time (RSET) are often misapplied without experimental backing.

Due to these issues, it's questionable whether PBD truly improves fire safety, which only becomes apparent when a fire actually occurs.

Moreover, the PBD process is time-consuming and resource-intensive. Designers must submit detailed fire strategies, including CFD and evacuation model results, for approval by AHJ. This process has significant challenges:

- **High Resource Demand**: Each PBD case requires substantial time and human resources for design, documentation, and approval.
- **Outdated Criteria**: Many criteria used in PBD are based on limited early fire tests and simulations, raising concerns about their applicability to modern buildings.
- **Manipulation of Models**: Fire engineers and designers may "tune" parameters in fire models to meet approval standards, bypassing scrutiny from authorities.

To address these challenges, AI and big data can offer future solutions, optimizing fire safety designs and regulatory processes.

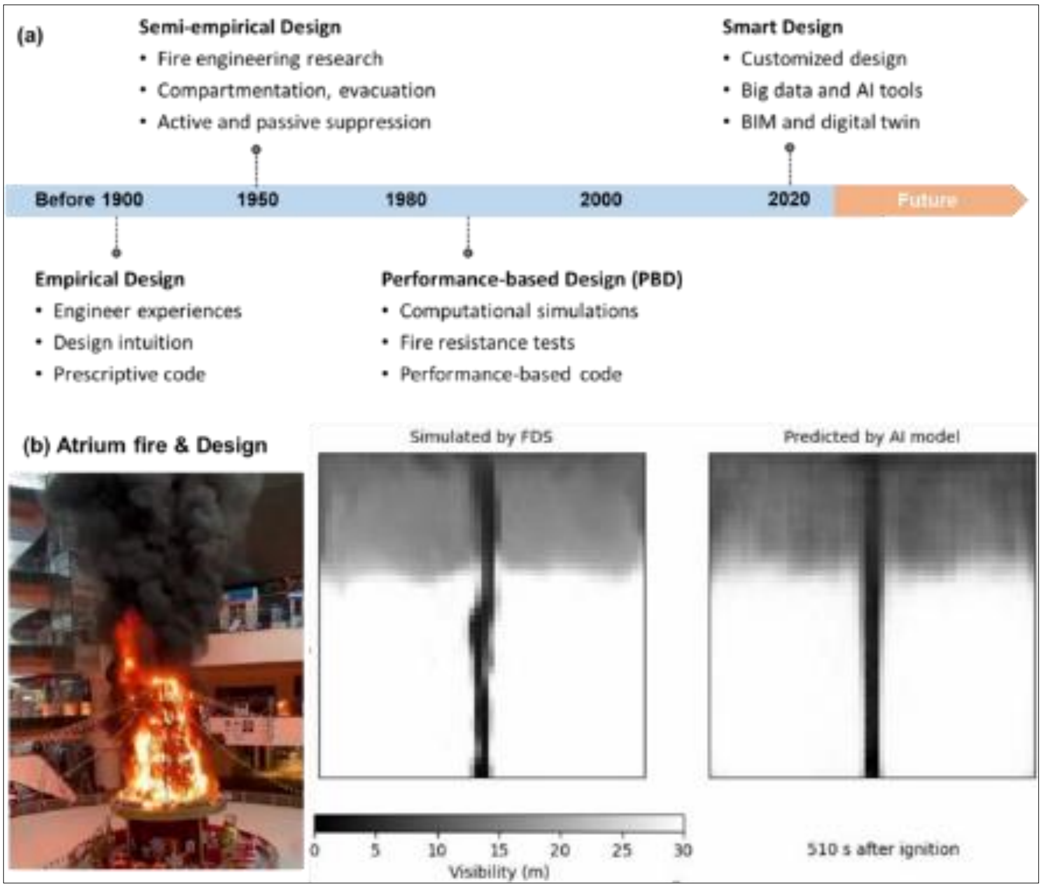

Figure 7 Building Fire

3.2. AI-Powered Design Process

AI's pattern recognition capabilities can potentially streamline fire safety design by reducing redundancy, improving safety, and cutting costs. The foundation for such applications lies in establishing a large fire scenario database and training AI models. For example, the movement of smoke in an atrium depends on factors like geometry, fire size (HRR), and ventilation conditions (Fig. 7b). These variables can be simulated to create a large fire scenario database for AI model training.

While it may take time to construct such a database, once trained, AI models can be packaged into software for use by both designers and AHJ. Similar to the development of CFD tools, these AI models can undergo years of development and refinement before becoming commercial products. AI-based PBD generally includes three stages:

- **Data Pre-Processing and Database Establishment**: Key input parameters like HRR, geometry, and smoke-ventilation designs are selected, and thousands of numerical simulations are run.
- **AI Prediction**: Given the input data, the AI model can predict the entire fire process, including smoke motion and visibility, in just seconds.
- **Output and Application**: AI outputs can calculate ASET, compare it with PBD requirements, and suggest optimal design options based on parameters like fire size and ventilation.

By replacing the trial-and-error process of CFD modeling, AI can dramatically reduce the time and effort involved in fire safety design. AHJs can also use these AI tools to quickly verify conventional PBD designs without running their own CFD models. This could reduce the design and review process from months to hours or even minutes.

3.3. AI in Atrium Fire Design

One application of AI in PBD is the design of fire safety measures for atrium fires, where AI can predict ASET values based on numerous fire scenario simulations (Fig. 7a) [50]. Rather than repeatedly running CFD simulations to determine limiting design conditions, AI can quickly generate thousands of fire scene images over space and time. It can then assess whether the given fire parameters meet fire safety codes.

Additionally, AI can optimize multi-dimensional parameters for various fire scenarios, building geometries, and safety codes. The Intelligent Fire Engineering Tool (IFETool) [51] is an AI-based design software currently in development, which is expected to enhance future fire safety designs for diverse buildings. This tool, backed by a growing numerical database, is expected to significantly improve building fire safety through AI's optimization capabilities, while also reducing the cost of design, construction, and installation.

3.4. Building-Fire Digital Twin

The traditional fire protection systems in buildings, which connect fire alarms, smoke detectors, and sometimes pressure information from sprinkler systems, are effective for early fire detection and alarm but offer limited support for fire prevention and real-time monitoring of fire scenes, evacuation, and rescue processes. To significantly enhance building fire safety, integrating a comprehensive digital twin with all fire-safety related sensors and the building information system is essential (Fig. 8).

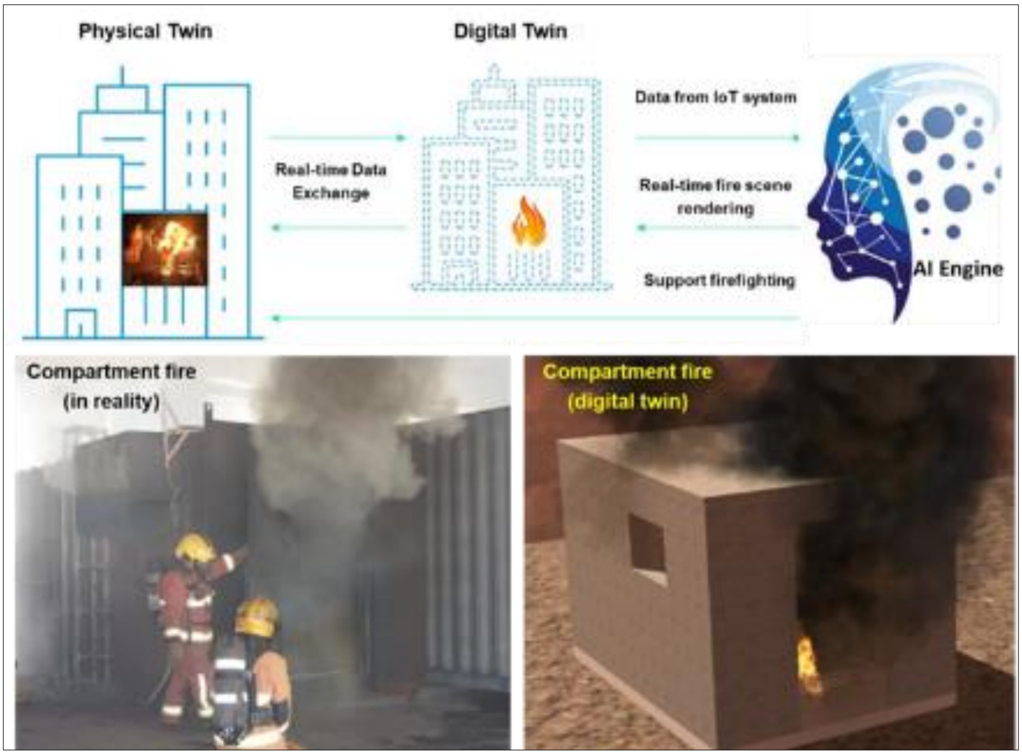

Figure 8 Fire Design Process

3.5. Concept and Development of Digital Twin

The concept of the Digital Twin originated in the early 2000s, with NASA pioneering its use to improve spacecraft simulation models in 2010. Today, digital twins are applied in various fields, including aircraft engines, manufacturing processes [52], and large infrastructures such as smart buildings and wind turbines. However, the technology is still evolving and not yet fully mature.

In the context of building fire safety, a Digital Twin is established based on the Building Information Model (BIM) during the design stage. It incorporates data from all sensors and cameras connected via the Internet of Things (IoT). For existing buildings without BIM, a Digital Twin can be created using MicroGIS, Computer Vision, and 3D virtual reality models, though integrating these diverse technologies remains challenging due to differences in software, programming languages, and communication protocols.

3.6. Enhancing Building Fire Safety with Digital Twin

A well-developed Digital Twin for fire safety involves the following features:

- **Integration of Fire Risk Information**: The Digital Twin is regularly updated with fire risk information, including fuel loads and the transport of hazardous materials within the building.
- **Real-Time Fire Scene Visualization**: During a fire event, acquiring detailed information from the fire scene is challenging due to heavy smoke and the rapid spread of fire. Conventional smoke and heat detectors provide limited information beyond detection.
- **AI and Digital Twin Integration**: The Digital Twin is linked to a pre-established fire database used to train an AI engine. This database includes thousands of CFD-based fire simulations, experimental data, and empirical correlations specific to the building. Real-time data from temperature sensors and cameras are fed into the AI engine, which quickly recognizes, visualizes, and renders the fire scene in the Digital Twin.
- **Case Study**: A demonstration system developed for compartment fire backdraft tests in the Hong Kong Fire Services Department illustrates this concept (Fig. 8). The system uses 16 thermocouple sensors installed in a test chamber to monitor temperature distribution. The data is sent to the cloud and processed by an AI engine pre-trained with experimental and CFD data. The AI quickly identifies the fire scenario and updates the Digital Twin for real-time monitoring.
- **Advanced Systems**: More sophisticated Digital Twin systems can be integrated into existing HVAC systems and sensor networks for larger and more complex buildings. This integration allows for real-time monitoring of fire scenes and behind smoke screens, enhancing emergency response and firefighting operations.

In summary, building-fire Digital Twins, supported by AI and comprehensive fire databases, offer a transformative approach to fire safety. They enable real-time visualization and analysis of fire scenarios, improving emergency response and overall building safety management.

4. Smart Fire Forecast and Fighting

Traditional firefighting methods have often lacked integration with live sensor data or advanced technologies like Digital Twins. This limitation is due to inadequate information collection, inaccurate fire modeling, and slow communication systems. However, recent advancements have introduced new approaches to enhance firefighting strategies, including data-analysis techniques and the deployment of sensors during fire events.

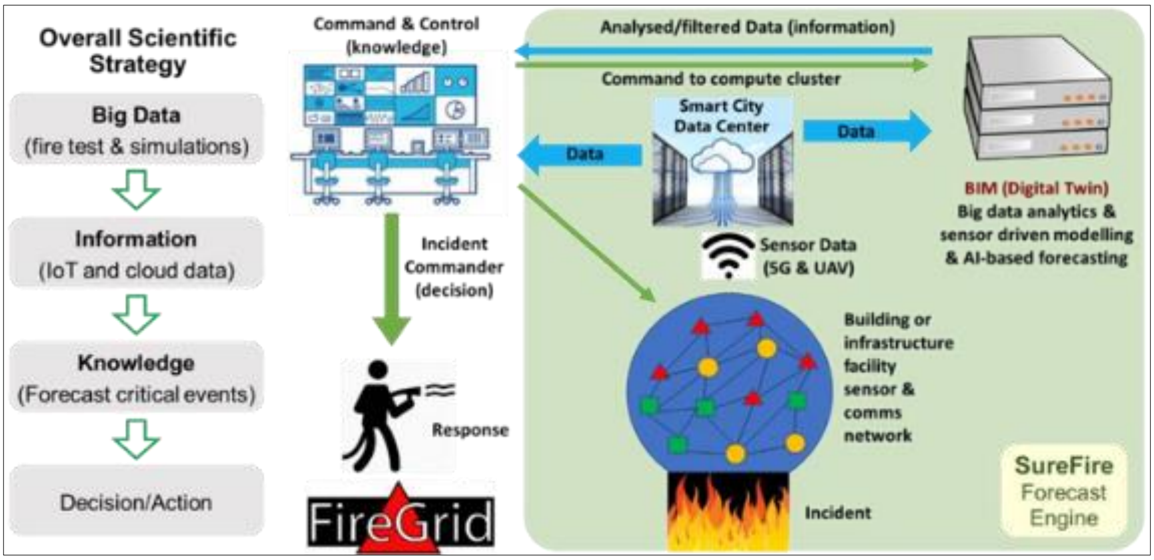

Figure 9 Fire Forecasting and Fighting

4.1. Evolution of Fire Forecasting Systems

4.1.1. Early Fire Forecasting Systems:

The 1st-generation FireGrid system was an early attempt to apply the principles of weather forecasting to fire prediction. It utilized sensor data and the K-Crisp Zone Model [56] to provide real-time fire forecasting with a lead time of up to 10-15 minutes, specifically for small-scale, post-flashover fires in apartments. While it demonstrated the potential for real-time forecasting, its accuracy was limited by the zone model and its applicability to larger or more complex fire scenarios.

4.1.2. Limitations of CFD Models:

Computational Fluid Dynamics (CFD) models offer more accurate predictions of fire behavior compared to zone models. However, they require extensive sensor data and can be computationally intensive, often taking hours or days to complete simulations. This makes real-time application challenging, especially in complex buildings where the data required to drive CFD models may be insufficient or impractical to collect in real time.

4.2. Advances with Digital Twin and AI

4.2.1. Digital Twin Integration

The concept of a Digital Twin, when coupled with an AI engine like the SureFire Forecast Engine (Fig. 9), represents a significant advancement in fire forecasting. Once a building's Digital Twin is established and operational, it can be used to predict fire evolution with greater precision and in real-time. This approach enhances the ability to forecast critical events such as:

- **Flashovers**: Sudden, intense fire behavior transitions.
- **Travelling Fires**: The progression of fire through different parts of the building.
- **Environmental Conditions**: Deterioration of conditions for residents and firefighters.
- **Structural Collapse**: The potential failure of building structures due to fire.

4.2.2. Real-Time Fire Forecasting Challenges

Achieving super real-time fire forecasting with lead times of 1 to 10 minutes involves overcoming several challenges:

- **Data Collection and Integration**: Ensuring that the Digital Twin receives accurate and timely data from a variety of sensors and sources.
- **Computational Efficiency**: Developing AI and machine learning models that can process data quickly and provide actionable predictions without the delay associated with traditional CFD simulations.
- **Model Accuracy**: Ensuring that the AI models are trained with comprehensive and representative data to accurately predict fire behavior and critical events.

In summary, the integration of Digital Twins and AI technologies holds the promise of transforming firefighting efforts by providing more accurate and timely forecasts of fire evolution. This advancement addresses the limitations of traditional methods and enhances the ability to anticipate and respond to fire-related challenges more effectively.

4.3. Development and Implementation of Smart Fire Forecasting and Fighting Systems

4.3.1. Development of Accurate Fire Forecast AI Algorithms

To enhance fire forecasting capabilities, an AI algorithm needs to be developed to predict critical fire events. The forecasting of fire growth and spread is a complex, nonlinear, multivariate spatiotemporal problem, akin to weather forecasting, involving variables such as wind, temperature, and air pollution. Here's how this can be approached:

- **Critical Event Library**: Develop a library based on big data analytics and AI/machine learning techniques. This library will set the goals and benchmarks for the fire forecast system.
- **Big Data-Driven Modelling Framework**: Create a framework and associated deep-learning algorithms to render fire scenes. Existing deep learning algorithms can be adapted, but the AI engine's structure and user interface should be optimized for fire forecasting applications.
- **Super Real-time Forecasting (SuRF)**: Implement a system that can predict the future fire scene inside a building with 10-15 minutes of advance notice, providing results within seconds. This includes:
- **Feature Extraction**: Process and filter data to extract relevant features.
- **Predictive Modelling**: Use models to forecast fire severity and spread.
- **Critical Event Prediction**: Incorporate additional AI models and surrogate models (e.g., empirical correlations, genetic algorithms, Kalman filters, Bayesian inferencing) to predict critical events like flashovers and structural collapses.
- **Integration with Fire Command Center**: Transfer critical information to the fire command center to support decision-making during firefighting and rescue operations.

4.3.2. Reliable Sensor Networks for Emergency Response

A robust sensor network is crucial for effective emergency response and smart firefighting. Here's how to establish and enhance these networks:

- **Integration with Building Automation System (BAS)**: Ensure that all sensors (e.g., thermocouples, cameras, smoke detectors) are integrated into the BAS. Existing sensors and networks can be upgraded for smart firefighting purposes.
- **Data Collection and Management**
  - **Temperature Sensors**: Existing energy-saving systems with temperature sensors can be utilized. During a fire, these sensors can switch to high-frequency data collection mode and feed data into the AI model.
  - **CCTV Cameras**: Security cameras can switch to emergency mode to capture and transmit information about smoke, fire, evacuation, and firefighter operations to the cloud data center, improving the accuracy of the Digital Twin.
  - **Advanced Sensors**: Install advanced sensors, such as IR cameras, laser scanners, Lidar, and gas and visibility sensors, in high-value infrastructure (e.g., tunnels, warehouses, museums, airports) for enhanced data collection.

4.3.3. Stable and Self-Healing Communication Networks

To support firefighting and rescue operations, a reliable communication network is essential:

- **Infrastructure Networks**
  - **Design and Installation**: Infrastructure networks should be part of the building services system, utilizing a combination of wired and wireless technologies (e.g., 5G, WiFi, ZigBee, Bluetooth) for balanced Quality-of-Service (QoS) and mobility.
- **Ad Hoc Networks**
  - Deployment of Breadcrumb MANET: Use a mobile ad hoc network (MANET) of small wireless sensor nodes (breadcrumb MANET) to establish temporary networks in the fire scene. These nodes can localize themselves, firefighters, and trapped individuals accurately.
- **Self-Healing Capabilities**
  - **Network Resilience**: Design the network to be self-healing, capable of adapting to damage caused by the fire and maintaining communication between sensors and the Digital Twin.

Combining AI-driven fire forecasting with robust sensor networks and resilient communication systems will significantly enhance smart firefighting capabilities, providing real-time insights and improving the effectiveness of emergency responses.

5. Conclusion

This chapter provides an overview of the advancements in applying AI technologies to fire safety engineering and smart firefighting. By comparing the historical use of Computational Fluid Dynamics (CFD) in fire engineering with the emerging AI-based approaches, a roadmap for the future of AI in fire safety is outlined. Key points include:

5.1. Construction of Reliable Training Databases

The development of large, reliable training databases using both experimental and numerical results is crucial for effective AI applications in fire safety.

5.2. AI Algorithms and Models

Various AI algorithms and models with significant potential for detecting and forecasting fire scenarios are discussed. These technologies are pivotal in advancing fire safety engineering.

5.3. Intelligent Firefighting Systems

Recent research on intelligent firefighting systems is reviewed, highlighting their potential to enhance fire safety and response.

The chapter proposes three innovative concepts for future intelligent building fire safety applications:

- **AI-Based Smart Fire Safety Design**

Utilizing a large fire database, AI can predict limiting design conditions within seconds. This capability helps minimize the cost of fire protection systems and provides sufficient justification for review by authorities having jurisdiction (AHJ).

- **Building-Fire Digital Twin**

By integrating IoT sensor networks, fire databases, and AI pattern-matching engines, a Digital Twin can render real-time visualizations of smoke-covered fire scenes within buildings. This approach enhances situational awareness during fire events.

- **Super Real-Time Fire Forecast**

Driven by the Digital Twin, a critical fire event library, and self-healing communication networks, AI forecast engines can predict fire development and critical events 5-10 minutes in advance. This capability supports firefighting and rescue operations and aids in decision-making during emergencies.

These concepts represent significant advancements in fire safety technology, offering improved prediction, visualization, and response capabilities in the face of fire emergencies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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